Early-Life Exposure to Traffic-Related Air Pollution and Risk of Development of Childhood Asthma

A Systematic Review and Meta-Analysis, a Novel Exposure Assessment Study and a Health Impact Assessment

Haneen Rami Inad Khreis, B.Sc. (Eng.), M.Sc. (Eng.)

Submitted in accordance with the requirements for the degree of
Doctor of Philosophy in Transport Studies

The University of Leeds, Faculty of Environment

Institute for Transport Studies

March 2018

The candidate confirms that the work submitted is her own, except where work which has formed part of jointly-authored publications has been included. The contribution of the candidate and the other authors to this work has been explicitly indicated below. The candidate confirms that appropriate credit has been given within the thesis where reference has been made to the work of others.

The jointly-authored publications include:

1. **Khreis** H, Kelly C, Tate J, Parslow R, Lucas K and Nieuwenhuijsen M (2017). Exposure to Traffic-Related Air Pollution and Risk of Development of Childhood Asthma: A Systematic Review and Meta-Analysis. **Environment International**, 100, pp. 1-31.

   I was responsible for conceiving and designing the study, performing and updating the searches, screening the abstracts and full-texts, extracting and verifying the data, undertaking the quality assessment, designing and conducting the meta-analyses, writing the initial draft, submitting it for publication and addressing all subsequent reviews and correspondence. Charlotte Kelly contributed to the conception and design of the study, independently screened 20% of the abstracts, independently extracted 10% of the data and offered advice on the meta-analyses. James Tate independently extracted 10% of the data. Mark Nieuwenhuijsen independently screened 50% of the full-texts, independently undertook the quality assessment and offered advice on the meta-analyses. All authors revised and critiqued the manuscript and approved its final version.

2. **Khreis** H and Nieuwenhuijsen M (2017). Traffic-Related Air Pollution and Childhood Asthma: Recent Advances and Remaining Gaps in Exposure Assessment Methods. **International Journal of Environmental Research and Public Health**, 14(3), 312.

   I was responsible for conceiving and designing the study, performing and updating the searches, screening the abstracts and full-texts, extracting and verifying the data, undertaking the quality assessment, writing the initial draft, submitting it for publication and addressing all subsequent reviews and correspondence. Mark Nieuwenhuijsen independently reviewed and extracted data for 50% of the studies, contributed to the interpretation of data *ad qualitative analysis, revised and critiqued the manuscript and approved its final version.*

3. Nieuwenhuijsen M, **Khreis** H, Verlinghieri E, Mueller N and Rojas-Rueda D (2017). Participatory Quantitative Health Impact Assessment of Urban and Transport Planning in Cities: A Review and Research Needs. **Environment International**, 103, pp. 61-72.
   I contributed to the design of the study, performed part of the literature review, drafted the section on “full-chain exposure assessment”, revised and critiqued the manuscript and contributed to addressing subsequent reviews.

4. **Khreis** H, Pellecuer L and Tate J (2017). Alternative Methods for Improved Vehicle Exhaust Emission Modelling and Impact on Local Road Transport Emission Inventories: The Case Study of Bradford, UK. **Transportation Research Part D: Transport and Environment**, under author review (September 2017).
   I was responsible for designing the study, performing the literature review, sourcing additional funding for, and overseeing the vehicle tracking survey, collecting, cleaning and verifying the data, selecting the vehicle categories to be modelled, coding the excel sheets, analysing the new emission model results, developing the average-speed-emission functions, running and analysing the traffic model results, linking the traffic model results to new and standard average-speed-emission functions, writing the initial draft, submitting it for publication and addressing all subsequent reviews and correspondence. James Tate contributed to conceiving and designing the study, provided the average vehicle fleet specifications used in the new emission model and ran the new emission model. Luc Pellecuer contributed to the analysis on influence of speed and segment length on emissions. All authors revised and critiqued the manuscript and approved its final version.

5. **Khreis** H, De Hoogh K, Zietsman J and Nieuwenhuijsen M (2017). The Impact of Different Validation Datasets on Air Quality Modelling Performance. **Transportation Research Record**, accepted.
   I was responsible for conceiving and designing the study, performing the literature review, collecting, cleaning and verifying the data, running the models, analysing and validating their results, writing the initial draft,

submitting it for publication and addressing all subsequent reviews and correspondence. Kees De Hoogh supplied two of the validation data sets (the 'ESCAPE' and 'de Hoogh' data set) and offered advice on the set up and running of the dispersion model. Mark Nieuwenhuijsen offered advice on the analysis and interpretation of the results. All authors revised and critiqued the manuscript and approved its final version.

6. **Khreis** H, De Hoogh K and Nieuwenhuijsen M (2017). Full-Chain Health Impact Assessment of Traffic-Related Air Pollution and Childhood Asthma, **Environment International**, in press.
   I was responsible for conceiving and designing the study, collecting, cleaning and verifying the data, running the models, analysing and validating the results, running the health impact assessment, writing the initial draft and submitting it for publication. Kees De Hoogh supplied the ESCAPE data set and offered advice on the set up and running of the dispersion model. Mark Nieuwenhuijsen offered advice on the health impact assessment analysis and interpretation of the results. All authors revised and critiqued the manuscript and approved its final version.

7. **Khreis** H, Warsow K, Verlinghieri E, Guzman A, Pellecuer L, A Ferreira, Jones I, Heinen E, Rojas-Rojas D, Mueller N, Schepers P, Lucas K and Nieuwenhuijsen M (2016). Urban Transport and Health: Understanding Real Impacts, Underlying Driving Forces and Co-Producing Future Directions. **Journal of Transport and Health**, 3(3), pp.249-267.
   I was responsible for conceiving and designing the study, performing the literature review, overseeing all communications, workshops and co-author inputs, writing the initial draft, submitting it for publication and addressing all subsequent reviews, correspondence and dissemination. All authors revised and critiqued the manuscript and approved its final version.

The solely-authored publications include:

8. **Khreis** H (2017). Critical Issues in Estimating Human Exposure to Traffic-Related Air Pollution: Advancing the Assessment of Road Vehicle Emissions Estimates. **Transportation Research Procedia**, accepted.

The listed publications form part of this PhD work and contain elements from Chapters 1, 2, 3, 4, 5 and 6. The candidate hereby declares that she made the major intellectual contribution to these papers; the joint authors were her PhD supervisors, her department colleagues and collaborators from other institutes who offered critique and advice at various stages of the research process, proof-read and commented on drafts of the submitted manuscripts.

Acknowledgements

My first and last thanks and an awful lot of appreciation go to Nadia: my mother, my best friend and my favourite scientist. Thanks to my father, my sister and my brother, Rami, Shadin and Badir, for their constant support and encouragement throughout this journey and for being so proud.

Many thanks go to my supervisors: James Tate, Karen Lucas and Roger Parslow for their help and their guidance.

Producing this thesis would not have been possible without the advice and insight of several people coming from other disciplines. Charlotte Kelly, Mark Nieuwenhuijsen, Natalie Mueller and David Rojas-Rueda, are wholeheartedly thanked for helping me take my very first steps in conducting systematic reviews, meta-analyses and health impact assessment and for providing constructive feedback on different stages of this project. I am also thankful to Kees de Hoogh who shared his valuable knowledge and experience in setting up and running dispersion and land-use regression models.

My appreciation goes to multiple people at Leeds City Council and City of Bradford Metropolitan District Council for sharing access to their datasets and models and for answering my recurrent queries. These are Richard Crowther, Neil Moore, Naveed Ahmed and Sally Jones. I am further grateful to the Information Technology teams at the Leeds Institute for Transport Studies (ITS) and the Barcelona Institute for Global Health (ISGlobal), specifically Fahed, Liam, David from ITS and Paco, Jose and Ruben from ISGlobal, who helped me install and run my (super slow) dispersion models and supplied me with multiple computers which were most needed to finish in time. The Geographical Information Systems team at ISGlobal, specifically Antonia, Marta and Montserrat are thanked for answering my queries and for their most valuable support in developing the SATURN snapping method.

I thank Philadelphia University, Jordan, for funding my study. I would also like to express my gratitude to the grant received under Category II of the World Conference on Transport Research Society’s Young Researchers Initiative, which advanced the vehicle tracking survey and emission modelling parts of this thesis. Many thanks to Tony May for pointing out this opportunity, and for his following constructive comments on my proposal and paper. A big thank you goes to my examiners Audrey de Nazelle (Imperial College London) and Gordon Mitchell (Leeds School Geography) for their constructive comments and a thought-provoking viva exam.

Last but not least, I acknowledge many wonderful friends, in Leeds and Barcelona, for their love, kindness and support and for sharing with me many stimulating chats and memorable moments, which made the time of my PhD not only bearable, but enjoyable, meaningful and enriching: Mark, Sanna, Chiara, Ersilia, Arwa, Jing, Magda, Alvaro, Peter, Angela, Natalie, Ione and Ita. We did grow together!

Abstract

Asthma is the most common chronic disease of childhood. In this thesis, I investigated whether there is an association between traffic-related air pollution (TRAP) and the development of childhood asthma, quantified the magnitude of this association and estimated its public health impact in Bradford, UK. For these purposes, I conducted a systematic review and a meta-analysis. I then developed a new vehicle emission model to estimate traffic NO_x and compared it to the standard European model. Subsequently, I set up and validated two full-chain health impact assessment models; linking distinct traffic, emissions, atmospheric dispersion and health impact models. Each full-chain model was underlined by a different vehicle emission model, the new and the standard one, and as such I tested the sensitivity of final air quality and health impact estimates to the vehicle emission estimates. I estimated the childhood population exposure to NO_2 and NO_x at the smallest census tract level and quantified the annual number of asthma cases associated with these exposures, whilst disentangling the impacts of traffic-related NO_2 and NO_x, and also the impacts of traffic-related NO_2 and NO_x specifically from minor roads and cold starts. I compared the full-chain models' estimates to estimates from commonly used land-use regression models which further provided exposure and health impact estimates for black carbon, $PM_{2.5}$ and PM_{10}. I quantified positive and statistically significant associations for black carbon, NO_2, $PM_{2.5}$, PM_{10} and risk of childhood asthma. The association with NO_x was positive but not statistically significant. I showed that the new vehicle emission model, as compared to the standard model, resulted in different source apportionment and higher emissions at low average speeds. These differences, however, did not translate into meaningful differences in air quality or health impacts, partly due to limitations in the traffic data which underestimated congestion. The full-chain models estimated NO_2 and NO_x with satisfactory predictive power but resulted in lower exposures and health impacts as compared to land-use regression. I estimated that 15% to 38% of all asthma cases in Bradford may be attributable to air pollution. Up to 6% and 12% of all cases were specifically attributable to TRAP, with and without minor roads and cold starts, respectively, but this percentage was underestimated. Full-chain health impact modelling was demonstrated as a valuable but underutilized tool to estimate the burden of disease associated with TRAP and to test the impacts of specific policy scenarios with a

temporal and/or spatial element. There is a further need to improve the feasibility, utility, resolution and validity of the supporting data and the full-chain modelling approach, especially by addressing its underestimation of TRAP, and consequently, the associated health impacts.

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List of Abbreviations

ADMS-Urban	Atmospheric Dispersion Modelling System
ATC	Automatic Traffic Counters
BAMSE	Barn (children), Allergy, Milieu, Stockholm, an Epidemiology project
BC	Black Carbon / $PM_{2.5\ absorbance}$
BMI	Body Mass Index
BoD	Burden of Disease
CADC	Common Artemis Drive Cycle
CAN	Controller Area Network
CAPPS	The Canadian Asthma Primary Prevention Study
CASP	Critical Appraisal Skills Programme
CBMDC	City of Bradford Metropolitan District Council
CCAAPS	The Cincinnati Childhood Allergy and Air Pollution Study
CCCEH	Columbia Centre for Children's Environmental Health birth cohort study
CEAS	Childhood Environment and Allergic Diseases Study
CHS	The Children's Health Study
CI	Confidence Interval(s)
CO	Carbon Monoxide
COPERT	COmputer Programme to calculate Emissions from Road Transport
DALYs	Disability Adjusted Life Years
DEFRA	Department for Environment, Food & Rural Affairs
DfT	UK Department for Transport

DMRB	Design Manual for Roads and Bridges
EC	Elemental Carbon
EF	Emission Factor
EGR	Exhaust Gas Recirculation
ESCAPE	The European Study of Cohorts for Air Pollution Effects
FEV1	Forced Expiratory Volume in 1 second
GALA II	The Genes–environments and Admixture in Latino Americans
GASPII	The Gene and Environment Prospective Study in Italy
GBD	Global Burden of Disease study
GHGs	Greenhouse Gases
GINIplus	German Infant study on the influence of Nutrition Intervention plus air pollution and genetics on allergy development
GIS	Geographical Information Systems
GPRD	General Practice Research Database
GPS	Global Positioning System
HBEFA	Handbook of Emission Factors for Road Transport
HDVs	Heavy Duty Vehicles
HIA	Health Impact Assessment
ICD	International Classification of Diseases
IgE	Immunoglobulin E
LAEI	London Atmospheric Emission Inventory
LDVs	Light Duty Vehicles
LEZ	Low Emission Zones
LISAplus	Life style Immune System Allergy plus air pollution and genetics
LUR	Land-Use Regression
MAAS	The Manchester Asthma and Allergy Study

MeDALL	The Mechanisms of the Development of Allergy
Medi-Cal	California Medical Assistance Program
MVCs	Motor Vehicle Crashes
NA	Not Applicable
NAEI	UK National Atmospheric Emissions Inventory
NEDC	New European Driving Cycle
NHS	National Health Service
NO	Nitrogen Oxide
NO_2	Nitrogen Dioxide
NO_x	Nitrogen Oxides
NTM	National Transport Model
OP	Oxidative Potential
ORs	Odds Ratios
PAF	Population Attributable Fraction
PCU	Passenger Car Units
PEF	Peak Expiratory Flow rate
PEMS	Portable Emission Measurement Systems
PM	Particulate Matter
PM_{10}	Particulate Matter equal or less than 10 micrometres in diameter
$PM_{2.5}$	Particulate Matter equal or less than 2.5 micrometres in diameter
PM_{coarse}	Particulate Matter between 2.5 and 10 micrometres in diameter
ppb	Parts per billion
PRISMA	The Preferred Reporting Items for Systematic Reviews and Meta-Analyses
PROSPERO	International Prospective Register of Systematic Reviews
RSD	Remote Sensing Device

SAGE	The Study of Asthma, Genes and the Environment
SAGE II	The Study of African Americans, Asthma, Genes and Environments
SATURN	Simulation and Assignment of Traffic to Urban Road Networks
SCR	Selective Catalytic Reduction
SE	Standard Error
SES	Socio-Economic Status
SORA	Study on Respiratory Disease and Automobile Exhaust
TAG	The Traffic, Asthma and Genetics Study
TEMMS	Traffic Emission Modelling and Mapping Suite
TfL	Transport for London
TRAP	Traffic-Related Air Pollution
TRL	Transport Research Laboratory
VESTA	Five (V) Epidemiological Studies on Transport and Asthma
WHO	World Health Organization
WLTP	Worldwide harmonized Light Vehicles Test Procedures
Y.O.	Years Old
YLDs	Years Lived with Disability
YLLs	Years of Life Lost

1 Background, Aims and Methodological Framework

1.1. The Wider Context

Clean air is a basic physiological necessity for human health and well-being. Nonetheless, air pollution is a significant threat to human health, worldwide (World Health Organization, 2006), and has been cited as the single biggest environmental health risk (Vidal, 2014). Traditionally, air pollution was recognized as an issue associated with domestic heating, coal burning and industrial emissions (Vardoulakis et al., 2003). In present urban areas, however, outdoor air pollution has become dominated by road traffic dust and tailpipe emissions (Anderson et al., 2013, European Environment Agency, 2007). Traffic-related emissions and air pollution, and subsequent exposures, are highly variable in space and time due to the motor vehicles' mobility; the uncertain and variable estimates of exhaust and non-exhaust traffic emissions; complex dispersion factors and the movement of people during leisure and daily activities. The cultural and often economic dependence on motor vehicles in combination with the increasing proportion of the population living and working near busy highways and busy urban roads has resulted in a greater number of people exposed to Traffic-Related Air Pollution (TRAP). This exposure puts more people at risk of numerous adverse health effects (Health Effects Institute, 2010).

In recent decades, the number of epidemiological studies showing TRAP as a public health problem grew substantially (Health Effects Institute, 2010, Khreis et al., 2016). Research studies demonstrates a robust association between TRAP and premature mortality (Beelen et al., 2014, Héroux et al., 2015, Hoek et al., 2013, Health Effects Institute, 2010). TRAP has also been associated with a wide spectrum of diseases, including, but not limited to, cardiovascular disease (Cesaroni et al., 2014); lung cancer (Raaschou-Nielsen et al., 2013, Health Effects Institute, 2010); diabetes (Eze et al., 2015); adverse birth outcomes such as premature birth, low birth weight, and perinatal mortality (Pedersen et al., 2013, Health Effects Institute, 2010, Sapkota et al., 2012) and adverse respiratory outcomes, especially in childhood, such as respiratory infections, decrements in lung function, chronic obstructive pulmonary disease and asthma (Health Effects Institute, 2010, MacIntyre et al., 2014b, Gehring et al., 2013, Eeftens et al., 2014, Anderson et al., 2013).

Exposure to TRAP in early life is of particular importance to infants and children, who are more susceptible to the hazardous effects of air pollution due to various reasons including their immature detoxification, immune and respiratory systems; their higher respiratory rates and their higher activity levels and time spent outdoors; where exposure to TRAP is generally elevated (Braback and Forsberg, 2009, Wright and Brunst, 2013). For example, at birth, the human lung and bronchial tree are not well-formed, and the development of its full functionality does not occur until approximately 6 years of age (Schwartz, 2004). The lung volume continues to increase through adolescents, until 18 years of age (Ritz and Wilhelm, 2008). The respiratory rate of infants and children is 3 times faster than that of adults and their ventilation rate is up to 66 times greater (Wright and Brunst, 2013). As such, both infancy and childhood, from birth to 18 years old, represent exposure windows that are crucial for some medical endpoints, including respiratory diseases. Exposure during these critical windows of time (or life periods) can result in permanent changes to the body's structure and function and, therefore, have life-long effects (Vrijheid et al., 2014).

The focus of this research was to assess 1) the risk (by producing meta-analytic risk estimates) and 2) the public health burden (by producing burden of disease estimates) of childhood asthma (from birth to 18 years old) associated with and attributed to TRAP exposures.

1.2. Background

Asthma is a chronic inflammatory disease of the air passages leading to and from the lungs and is cited as the most common chronic disease of childhood (Gasana et al., 2012, Fabian et al., 2012, Gaffin and Phipatanakul, 2014). Childhood asthma prevalence in the UK is high and ranges between 17% and 23% (National Institute for Clinical Excellence, 2007). Amongst other paediatric long term conditions, asthma accounts for the highest number of emergency bed-days and emergency hospital admissions (Yorkshire and Humber Public Health Observatory, 2012): a child is admitted to hospital every 20 minutes because of an asthma attack (Asthma-UK, 2014). In 2007/2008, for example, there were 32,030 emergency bed-days in England for children and young people aged under 19 years old with a primary diagnosis of asthma (Yorkshire and Humber Public Health Observatory, 2012). Every year, the National Health Service (NHS) spends £1 billion treating and caring for asthmatics (Asthma-UK, 2014)

Clinically, asthma has heterogeneous phenotypes. Yet, the condition can be principally characterized by a reversible airflow limitation, bronchial hyper-responsiveness[1] and airway inflammation (McCunney, 2005, Corren, 2013, Ishmael, 2011). The dominant process that leads to clinical symptoms is smooth muscle contraction and airway inflammation, accompanied by an over production of mucus, which result in the airflow limitation and obstruction (Ishmael, 2011). The inflammatory process affects the entire tracheobronchial tree and can cause severe episodic airflow obstruction (asthma attacks), shortness of breath, coughing and wheezing (Saetta and Turato, 2001, Ober and Yao, 2011). These processes and symptoms have a significant impact on quality of life of affected children and their caregivers as they restrain school and outdoor play; cause absenteeism; night and sleep disturbance (National Institute for Clinical Excellence, 2007) and impose a burden on caregivers to monitor symptoms and administer medication (Halterman et al., 2004).

A clinical diagnosis of asthma is based on Forced Expiratory Volume in 1 second (FEV_1), Peak Expiratory Flow rate (PEF) and reported symptoms including coughing; difficulty breathing; chest tightness; shortness of breath and wheezing (Ishmael, 2011, Yawn, 2008, Weir, 2008); whilst excluding other causes of recurrent respiratory symptoms (National Institute for Clinical Excellence, 2007). From this symptoms' list, prospective follow-up studies demonstrate that wheezing is, to some degree, a predictive factor of later asthma (Hyvärinen et al., 2005, Piippo-Savolainen and Korppi, 2008, Piippo-Savolainen et al., 2004).

Due to the transient and reversible nature of asthma and its non-specific symptoms which are shared with other disease processes, the condition is generally under-diagnosed and under-treated (Karadag et al., 2007, Okoromah and Oviawe, 2002, Speight, 1978, Weir, 2008, World Health Organization, 2013). This is particularly true in children where objective clinical tests are difficult to perform due to compliance difficulties (Weir, 2008). Further, the under-representation of patient symptoms to clinicians, low parental attention and low access to health centres play an important role in under-diagnoses (Zejda et al., 2013, van Schayck and Boudewijns, 2017).

Over the past three to four decades, the global prevalence of asthma has been on the rise (Anandan et al., 2010, Gasana et al., 2012, Pearce et al., 2007, World Health Organization, 2013). More than 358 million people have asthma, globally (van

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[1] A state characterized by easily triggered contraction of the bronchioles (small airways).

Schayck and Boudewijns, 2017). No explicit explanations of these relatively rapid increases exist (Brauer et al., 2002, Clark et al., 2010, World Health Organization, ND), but it is unlikely that genes which modify the susceptibility to asthma have changed over this relatively short time period (Cookson, 2004). Several plausible theories have been put forward to explain these recent increases in the prevalence and incidence of the disease (Brunton and Saphir, 1999, Baldi et al., 1999, Brooks et al., 2013, Byrd and Joad, 2006, Bernstein, 2012), all of which theorize that the observed increases are attributable to recent environmental changes. Amongst the suggested theories and explanations is the potential contribution of ambient air pollution in promoting the disease, especially when the exposure takes place in the early years of childhood (Bernstein, 2012, Baldi et al., 1999, Byrd and Joad, 2006).

Until relatively recently, the common wisdom about air pollution and asthma was that air pollution can exacerbate pre-existing asthma across a variety of outcomes; such as increasing rates of asthma hospitalizations, emergency room visits and medication used (Schildcrout et al., 2006, Schwartz et al., 1993, Gauderman et al., 2002, Sunyer et al., 1997, Lierl and Hornung, 2003, Lipsett et al., 1997, Von Klot et al., 2002, Slaughter et al., 2003); but cannot cause the development of the disease (Eder et al., 2006). This school of thought was affirmed by various studies that showed the prevalence and incidence rates of asthma to generally be not greater in communities with higher levels of regional air pollution (McConnell, 2013, Heinrich et al., 2002).

In recent years, however, the research community has produced multiple studies which suggested an association between living near busy roads or high levels of traffic activity and TRAP and the prevalence or incidence of childhood asthma (see Chapter 2). As eloquently phrased by McConnell (2013) at the 2013 Symposium on Cumulative Impacts and Children's Environmental Health:

> *'…I think we've been looking for the last thirty years at the wrong pollutant mixture (referring to regional and not traffic-related air pollution) and I also think as you'll see, I think that that history has got in the way of advancing our understanding of the role of air pollution in asthma, and has limited our approach to risk assessment…'*

The research on TRAP and asthma onset has picked up momentum recently and witnessed several advances. First, although several studies investigated the associations between air pollution and asthma exacerbations or asthma prevalence at one point in time, the evidence for the effect of exposure to TRAP on asthma onset was considerably less developed. This particular research area has seen an epidemic recent increase in the number of published studies, with 19 (out of 42 studies) published after 2014 (Khreis and Nieuwenhuijsen, 2017).

Second, to define the exposure and study its effects, earlier studies on the associations between TRAP and asthma relied on air pollution data from fixed-site monitoring stations and/or proximity analysis and measures such as distance to major roads or traffic intensity within buffer zones (English et al., 1999, McConnell et al., 2006, Zmirou et al., 2004, Shima and Adachi, 2000, Shima et al., 2003, Shima et al., 2002). With the further development of Geographic Information Systems (GIS) applications and other sophisticated modelling packages capable of simulating air pollution dispersion in ambient air, exposure assessment methods have undergone important changes, leading to a more accurate assessment of TRAP exposures and a new capacity to study the effects of actual pollutant and not just surrogates of TRAP (e.g. distance to major roads). More and more studies began to report positive associations between exposure to TRAP and the development of childhood asthma (Khreis and Nieuwenhuijsen, 2017). Yet, this evidence was never deemed sufficient (Health Effects Institute, 2010) and a synthesis of this rapidly growing evidence base has been missing from the literature since year 2010.

Since the Health Effects Institute (HEI) seminal Special Report 17 on '*Traffic-Related Air Pollution: A Critical Review of the Literature on Emissions, Exposure, and Health Effects*' (Health Effects Institute, 2010), an updated synthesis focused on TRAP and the risk of childhood asthma development has been absent. Further and linked to this point, there was a lack of exposure-response functions based on systematic reviews and meta-analyses of relevant studies; something which limits the use of the relationship between TRAP and asthma onset to evaluate the burden of disease and/or the impact of transport policies on childhood asthma (Favarato et al., 2014).

Until now, it was only possible to generate meta-analytic exposure-response functions for commonly used pollutant metrics such as nitrogen dioxide (NO_2) but not for the plethora of traffic-related air pollutants because of the limited and heterogonous evidence base. As such, the very few previous Health Impact Assessment (HIA) studies assessing the burden of asthma attributable to TRAP relied on exposure-response functions from individual studies (i.e. single rather than a pooled meta-analytical estimate). These individual studies' exposure-response functions used proximity to traffic as the underlying exposure metric, lacked statistical precision and led to high statistical uncertainty in the range of the estimated impacts (Perez et al., 2009, Perez et al., 2013).

Moreover, research on TRAP and asthma development, as many other health outcomes, has been typically undertaken in at least two separate stages. Air pollution or traffic levels are often assessed by GIS, transport and air pollution modellers whilst health effects or impacts are often assessed by epidemiologists and health impact assessors. The holistic tailpipe-to-lungs spectrum has been rarely modelled and assessed in a comprehensive and continuous manner and there is a clear lack of full-chain HIA models (Nieuwenhuijsen et al., 2017, Texas A&M Transportation Institute, 2016).

In a full-chain model, the work considers the full-chain from the exposure source to the health endpoint and as such, traces the health impacts under investigation back to the responsible air pollution sources. The exposure is assessed starting from the source (e.g. traffic activity); to source emissions (e.g. traffic emissions); to resulting air quality and exposures (e.g. emissions dispersion and TRAP exposures) and finally to the associated health effects or impacts (e.g. new asthma cases) (Nieuwenhuijsen et al., 2017).

In practice, full-chain models could be obtained by coupling existing models of traffic, emissions, air pollution dispersion and exposure assignment, to estimate final human TRAP exposures and associated health effects or impacts.

This full-chain model approach has a key practical advantage: it makes an explicit link between the source of air pollution (e.g. urban road traffic, diesel versus petrol vehicles, heavy duty versus light duty vehicles etc.) and its impacts (e.g. childhood asthma cases). As such, the full-chain model approach allows analysing the environmental and health impacts of *specific* policy scenarios that are under or should be under consideration (e.g. reducing or spatially/temporally shifting urban road traffic, changing proportions and operations of diesel versus petrol vehicles, heavy duty versus light duty vehicles etc.). The current wall between the different disciplines and the chain's steps is significant, not only because it impairs explicit and specific policy scenario analysis and recommendation, but also because there are many steps and decisions to be made along this full-chain, or the parts of it, all of which have implications on the results, their validity and their utility. Therefore, the process is viewed here as important as the outcome as it can highlight the uncertainties in current scientific knowledge and practice and sheds light on open questions and potential for relevant advances.

Finally, key advantages of the full-chain model approach can be realized in future research that assesses the environmental and health impacts of traffic and transport policy scenarios that have a clear temporal or spatial element, and/or research that requires refined spatial-temporal estimates of TRAP to add them onto time activity patterns and belter capture human exposure variability and its health impacts. Although these important areas of application were not explored, and were beyond the scope of the current study, the methodology presented here paves the way for such analyses.

With childhood asthma reaching epidemic proportions in some regions and with road traffic continuing to be the principal source of air pollution in urban areas, a clearer understanding of the interactions between TRAP and the onset and burden of the disease is a priority. Such an understanding may further our knowledge of the potential mechanisms of asthma development and the complex interplay between genetic and environmental factors and may offer some explanation of the relatively rapid changes in asthma prevalence, in times when TRAP became more dominant. The burden of asthma specifically attributable to TRAP has also been rarely quantified and although the individual asthma risks associated with TRAP can be relatively small, the public health consequences can be significant, but are yet underexplored.

1.3. Aim and Objectives

The overarching aim of this research study has been ***to estimate the impact of TRAP exposures on the development of new cases of childhood asthma using full-chain health impact assessment models complemented with meta-analytic exposure-response functions and a novel vehicle emissions assessment methodology***. The specific objectives of this research study were six-fold, as outlined below. These objectives were met in the respective chapters (in brackets):

Box 1. Research Objectives and Corresponding Chapters

- **Objective 1 →** To investigate whether early-life exposure to TRAP can drive the subsequent development of asthma in children from birth to 18 years of age (Chapter 2)
- **Objective 2 →** To investigate pollutant-specific effects and provide appropriate pollutant-specific meta-analytic exposure-response functions that can be used in health impact assessment (Chapter 2)
- **Objective 3 →** To develop a new more reliable vehicle emission model and compare it to the standard vehicle emission model used in road transport emission inventory estimation (Chapter 4)

- **Objective 4 →** To develop a full-chain exposure assessment model linking traffic, emissions and atmospheric dispersion models and estimate TRAP exposures in a UK case study (Chapters 3, 4 and 5);
- **Objective 5 →** To estimate the burden of childhood asthma attributable to TRAP assessed in the UK case study (Chapter 6);
- **Objective 6 →** To explore whether different exposure assessment methods and different vehicle emission assessment methodologies translate into different estimated disease burdens (Chapter 6);
- **Objective 7 →** To highlight knowledge gaps and systematically outline the uncertainties at each step of the full-chain modelling; overview alternatives and highlight research and practice needs to advance the current state-of-art (Chapter 7).

1.4. Overall Methodology

The overall methodological framework of this research study is shown in Figure 1.

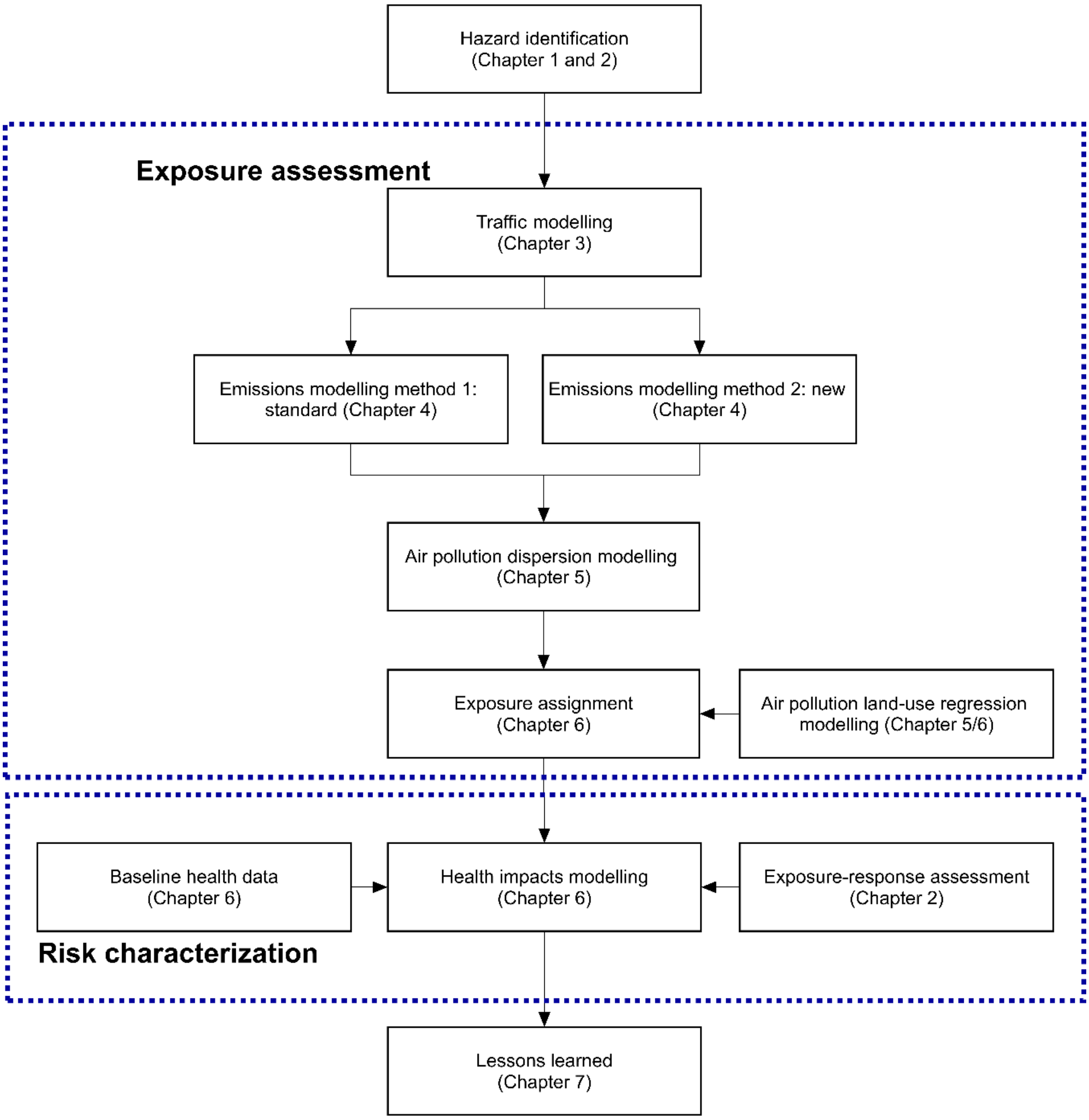


Figure 1 Full-Chain Health Impact Assessment of TRAP, Source: Modified after Nieuwenhuijsen et al. (2017)

To achieve objective 1, a comprehensive and up-to-date systematic review of available studies on the associations between TRAP exposures and the subsequent development of childhood asthma (birth to 18 years of age) was conducted (Chapter 2). This work contributed to the literature by providing the first updated synthesis focused on TRAP and the risk of childhood asthma development since the HEI report in 2010 (Health Effects Institute, 2010). The development of childhood asthma was defined as new asthma in previously healthy children when 1) reported between two or more follow-ups or 2) reported over the lifetime of the child in birth cohort studies or cross-sectional studies. Likewise, the case-control studies included either looked at lifetime asthma as a measure of asthma development (i.e. like birth cohort studies) or excluded children with a history of asthma in the control groups (i.e. like cohort studies). In all the included studies, the exposure to TRAP had to *precede* the outcome to ensure the correct temporal sequence of events. For example, associations between birth year exposure and lifetime asthma prevalence in cross-sectional studies were considered as associations between TRAP exposure and asthma development and hence such studies were included. As such, studies that investigate asthma incidence and those that investigate lifetime prevalence were included, as long as the exposure to TRAP *preceded* the outcome detecton in previously health children. This formulation is similar to previous methodology adopted by the Health Effects Institute (2010). The question of whether the increase in asthma incidence and/or lifetime prevalence in association to TRAP might represent added cases, an acceleration of the development of asthma or increased severity making the disease sufficiently apparent for clinical diagnosis is not addressed here and cannot be answered based on the current evidence.

To achieve objective 2, pollutant-specific meta-analyses were undertaken to explore pollutant-specific effects of TRAP on childhood asthma and understand the drivers of heterogeneity. The meta-analyses quantified the relationship between TRAP and the subsequent development of childhood asthma with increased precision providing appropriate exposure-response functions which were used in subsequent health impact assessment (Chapter 2 and 6). This work contributed to the literature by providing previously missing meta-analytic exposure-response functions for a plethora of traffic-related air pollutants in association with childhood asthma development.

To achieve objective 3, real-world driving cycles were directly collected from the study area of Bradford, UK, and these were used to model second-by-second vehicle emissions for the wide range of vehicles operating in Bradford. This modelled data underlined the development of a new emission model (a new set of average-speed-emission functions) which was compared to the standard approach and used to estimate the road transport emission inventory. This work contributed to the literature by exploring and developing alternative methods for local vehicle emission modelling and providing alternative emission estimates whose impacts on air quality and health impact estimates were studied. Across the full-chain, advancing the emission modelling stage received the most attention and effort. The key reasons behind this decision were: 1) the accumulating knowledge that standard methods to estimate vehicle emission factors, especially in urban settings, are substandard and underestimate real-world vehicle emissions, and therefore subsequent TRAP (see full literature review in Sections 4.1.2, 4.1.3 and 4.1.4); 2) the initial expectation that the underestimation of TRAP will result in significant underestimation of human exposure and associated health impacts, and therefore higher vehicle emission factors might result in higher and more realistic attributable disease burden and 3) practical considerations including the available time and resources such as the technical capacity and state-of-the-art equipment that were available at the Institute for Transport Studies to measures vehicle driving cycles and model instantaneous vehicle emissions. In hindsight, it is now clear that the new emission modelling methodology had very little impact on the attributable burden of disease and that improvements focused on other stages of the full-chain model might have yielded better estimates. However, the new emission modelling methodology, and linking it to highly resolved traffic data, can be extremely useful in other applications, which were beyond the scope of this research study. These include: 1) the assessment of traffic and transport policies that have clear temporal consequences, for example, altering the spatial and diurnal profiles of traffic flows, speeds or emissions and 2) complementing the more refined spatial-temporal estimates of TRAP with time activity patterns to better capture human exposure variability and study exposure misclassification that may result from standard assessment methods, for example, assigning exposures at the residential address or at the census tract level. Unfortunately, these issues could not be addressed within the scope of the current study, but the work presented here paves the way for such analyses.

To achieve objective 4, traffic, emissions and atmospheric dispersion modelling were undertaken using the two different emission models (newly developed versus standard). Each traffic, emissions and atmospheric dispersion models set were linked together in a novel full-chain exposure assessment model (Chapter 3, 4 and 5). This work contributed to the literature by developing the full-chain exposure models and validating them against multiple data sets.

To achieve objectives 4 and 5, TRAP in Bradford was estimated using the two full-chain exposure assessment models (linking a traffic model, with two different emission models and an atmospheric dispersion model). Estimated TRAP was spatially linked to census population data and new cases of asthma attributable to these exposures were estimated using standard health impact assessment methodology (Chapter 5 and 6). This work contributed to the literature by estimating the burden of childhood asthma attributable to exposures to air pollution, and specifically to its traffic-related component.

To achieve objective 6, the differences in the health impacts estimated using the two full-chain exposure assessment models were explored. Further, a third previously developed and commonly used Land-Use Regression (LUR) model was used to provide different exposure data and estimate new cases of asthma attributable to these exposures. These results were compared to results from the two full-chain models (Chapter 6). As asthma is generally under-diagnosed and under-reported, using baseline asthma incidence rates only, as has been done in the main HIA, is likely to under-report the burden of asthma due to TRAP. As such, another baseline wheezing incidence rate was used in sensitivity analysis. The baseline wheezing incidence rate related to wheezing disorders based on treatment, identified the existence of at least two drug prescriptions indicated for the treatment of asthma a minimum of 1 week and a maximum of 12 months apart. This work contributed to the literature by providing an indication of the impact of using different exposure models, different emission factors and different baseline incidence rates on the estimated health impacts.

At each step of the full-chain modelling (traffic modelling, emissions modelling, atmospheric dispersion modelling, exposure and health impact assessment), the decisions made, the uncertainties and potential errors were documented, critically overviewed and discussed, throughout the thesis. To achieve objective 7, a list of these decisions, uncertainties and potential errors, at each step of the modelling, and their potential or estimated impact and propagation through the full-chain was developed (Chapter 7). Alternative options and research and practice recommendations to improve the utility of available datasets and models were overviewed (throughout the thesis and Chapter 7).

1.5. Thesis Structure

The following paragraphs draw an overview of the contents of the present thesis. Due to the multiple and distinct topic areas which this thesis covered, each chapter was written to stand-alone as a complete micro-study with its own discrete literature review, methods, results and discussion section. The final chapter provided an overall and integrated interpretation of the thesis.

- Chapter 2 provides a description of the conceptual and methodological framework and steps that have been carried out to systematically synthesize and meta-analyse the evidence on the association between childhood exposure to TRAP and their subsequent risk of asthma. This research was published in Khreis et al. (2017d) and a follow-up study focused on exposure assessment methods in Khreis and Nieuwenhuijsen (2017).
- Chapter 3 provides a description of the work undertaken to obtain the Bradford traffic network characteristics, including modelling the traffic flows, the average traffic speeds and extracting road lengths and geographical locations from a previously established and validated traffic model. An independent validation exercise and diurnal scaling are further presented.
- Chapter 4 provides a description of the work undertaken to develop 167 new and vehicle specific, average-speed-emission functions (i.e. a new vehicle emission model) for Bradford to estimate the nitrogen oxide (NO_x) emissions. The average-speed-emission functions were developed for the full fleet of diesel and petrol passenger cars, diesel and petrol vans, buses, coaches and rigid and articulated trucks. The results of the new vehicle emission model were compared to the corresponding results of the standard vehicle emission model. Part of this research was funded by a Young Researchers' Innovation Grant from the World Conference on Transport Research Society and was accepted in a peer-reviewed conference paper in Khreis (2016). A fuller journal paper has also been submitted and the author is currently revising it in light of peer-review comments (Khreis et al., 2017b).
- Chapter 5 provides a description of the work undertaken to link the estimated traffic activity (Chapter 3) with the newly developed and the standard average-speed-emission functions (Chapter 4), to estimate NO_x emission inventories from the full fleet in Bradford. The chapter continues to describe the work undertaken to set-up and validate two air pollution dispersion models which converted the link-based emission rates into ambient air pollution concentrations of NO_x and NO_2. A comparison between these results and results from a commonly used LUR model is presented. Part of this research has been submitted as a journal paper, revised in light of peer-review comments and resubmitted (Khreis et al., 2017a). The other part is currently in preparation for another invited journal paper (Khreis et al., 2018).
- Chapter 6 provides a description of the work undertaken to assign the estimated air pollution concentrations to census tracts and population data,

and to then estimate the burden of asthma onset in relation to TRAP exposures; as assessed by different models (two full-chain exposure assessment models and a LUR model). Part of this research has been submitted as a journal paper and is currently under peer-review (Khreis et al., 2017c). The other part is currently in preparation for another invited journal paper, as above (Khreis et al., 2018).

- Finally, Chapter 7 is a qualitative systematic summary of the decisions made at each step of the full-chain modelling, the associated uncertainties, potential errors and an overview of alternative options. Policy implications of this work are also discussed.

2 Systematic Review and Meta-analysis

2.1. Background

Asthma is a complex and heterogeneous chronic inflammatory disease of the airways (Wenzel, 2012, Xie and Wenzel, 2013). Numerous studies show that the prevalence of childhood asthma has increased dramatically since the 1950s, with some suggestion of plateauing in developed regions (Anandan et al., 2010, Braman, 2006, Pearce et al., 2007, Anderson et al., 2007, Zhang et al., 2013, Huang et al., 2015, Chen et al., 2016). The factors driving these increases are largely unknown, but coinciding changes in environmental exposures such as changes in hygiene and air pollution are thought to be responsible (Gaffin et al., 2014).

One putative environmental exposure is humans' exposure to ambient air pollution. Although there is sufficient evidence that ambient air pollution can exacerbate pre-existing asthma across a variety of outcomes (Gilmour et al., 2006, Guarnieri and Balmes, 2014, Braback and Forsberg, 2009), such as increasing daily symptoms, rates of hospitalization, emergency room visits and medications used (Schildcrout et al., 2006, Schwartz et al., 1993, Sunyer et al., 1997, Lierl and Hornung, 2003, Slaughter et al., 2003), the role of air pollution exposure in the initial development of asthma is as yet contested (Eder et al., 2006, Gowers et al., 2012, Gehring et al., 2015b, Deng et al., 2016). This is partly because of the difficulty in conducting adequate epidemiological studies required to address this question.

Earlier reviews have effectively excluded ambient air pollution as a plausible cause of the rise in asthma incidence, with one argument being that the available evidence was inconsistent (Koenig, 1999). Furthermore, previous studies showed that asthma prevalence did not mirror changes in ambient air pollution concentrations: reductions in levels of sulphur dioxide (SO_2) and total suspended particles (TSP), for example, seemed to synchronize with rapid increases of the condition in some areas (Gowers et al., 2012, Eder et al., 2006, Heinrich et al., 2002, Anderson, 1997). However, positive associations were subsequently shown between incidence and prevalence of asthma and wheeze and exposure contrasts at the intra-urban scale, mainly dominated by TRAP (Gasana et al., 2012, Anderson et al., 2013, Bowatte et al., 2015, Health Effects Institute, 2010, Favarato et al., 2014). Traffic-related air pollutants necessitate specific examination as they are ubiquitous and are of different chemical and physical nature compared to the classical air pollution mix associated with domestic heating and power plants.

Early-life and childhood could represent critical exposure windows for asthma development due to the plasticity, susceptibility of target organs and systems during these developmental periods and the long maturation period of the respiratory, immune and detoxification systems (Schwartz, 2004, Wright and Brunst, 2013, Deng et al., 2015, Bateson and Schwartz, 2007). Moreover, when compared to adults, infants and children exhibit higher ventilation rates (Wright and Brunst, 2013), reduced nasal deposition efficiencies for inhaled particles (Bennett et al., 2007), are more typically mouth-breathers invalidating the nasal filtering and conditioning of the inhaled air in temperature and relative humidity (Bateson and Schwartz, 2007), and tend to be more active outdoors where exposure to TRAP is generally higher (Braback and Forsberg, 2009, Bateson and Schwartz, 2007).

Four meta-analyses were previously published on asthma and TRAP (Anderson et al., 2013, Bowatte et al., 2015, Gasana et al., 2012, Favarato et al., 2014). None of these analyses were specifically focused on TRAP exposures and childhood asthma development. For example, Gasana et al. (2012); Anderson et al. (2013) and their follow-up synthesis by Favarato et al. (2014), included both studies of TRAP exposures and childhood wheeze, and studies of TRAP exposures and asthma prevalence. Including both outcomes in the analysis may be misleading as childhood wheeze is a non-specific symptom, represents different disease patterns at different ages (Gehring et al., 2002, Piippo-Savolainen and Korppi, 2008, Brunst et al., 2015) and can feasibly preclude making a distinction between the onset of asthma and its exacerbation (Health Effects Institute, 2010). However, it is worth noting here that due to the complexity of asthma and its diagnosis (Section 1.2.), excluding wheeze is likely to result in underreporting the burden of asthma due to TRAP in the following analyses of this study.

Further, studies of TRAP exposures and childhood allergies and sensitization, included in Bowatte et al. (2015) were excluded from this research study as there is emerging evidence that the importance of allergy/atopy has been overemphasized and is much less relevant in asthma pathogenesis than previously supposed (Asher, 2011, Pearce et al., 1999, Douwes et al., 2002). Furthermore, Favarato et al. (2014) limited their inclusion criteria to a single traffic-related air pollutant (nitrogen dioxide), which limits the understanding of the potentially different effects of a wider range of traffic-related air pollutants.

This research study, in contrast to previous published meta-analyses, followed the state-of-the-art methodology adopted by the Health Effects Institute's (HEI) in 2010. HEI synthesized case-control and cohort studies published before October 2008 and specifically focused on TRAP exposures as a potential cause for childhood asthma development (Health Effects Institute, 2010). The relevant HEI's review was reported in a sub-section on childhood asthma development in Special Report 17: '*Traffic-Related Air Pollution: A Critical Review of the Literature on Emissions, Exposure, and Health Effects'* and this was the only published review specifically focused on TRAP exposure as a risk factor for childhood asthma development (Health Effects Institute, 2010). At the time, this review included 8 studies of exposure to traffic pollution and the incidence of doctor-diagnosed asthma in children. An updated evidence base has been missing from the literature since, although wider reviews (including other sources of air pollution, asthma symptoms, wheeze and allergic outcomes) mainly of quantitative nature (i.e. meta-analyses), have been previously published and were listed above. The HEI's review also included no formal meta-analysis as it was deemed inappropriate due to lack of equivalence among the exposures measures and populations studied. Then, the HEI's review panel considered the evidence of a causal relationship between TRAP and childhood asthma to be in a grey zone between *'sufficient'* and '*suggestive but not sufficient'*; depending on the weight one gives to the consistency and precision of results. As such, the question of whether exposure to TRAP can cause asthma in children remained open.

2.2. Chapter Objectives and Contribution to Literature

The objective of this research phase was ***to devise and undertake a systematic review to identify, appraise and synthesize the available evidence on the association between children's exposure to TRAP and their subsequent development of asthma and to further demonstrate where knowledge is lacking***. As such, this research phase contributed to the literature by providing an up-to-date evidence base concerned with the association between TRAP exposures (exposure) and the subsequent development of childhood asthma (outcome). The work highlighted research and knowledge gaps and provided input for a health impact assessment study which will be undertaken to estimate the air quality profile and annual childhood asthma cases attributable to TRAP in Bradford, UK.

2.3. Methods

This systematic review was conducted in accordance with established guidance on Undertaking Reviews in Health Care published by the University of York's Centre for Reviews and Dissemination (Akers et al., 2009). A protocol was registered on the International Prospective Register of Systematic Reviews (PROSPERO), documenting the methodological approach, a priori (Khreis et al., 2014). The Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) checklist (Stroup et al., 2000) was completed and can be found in the supplementary data of Khreis et al. (2017d). The review's question was: *'Does children's exposure to TRAP increase their risk of developing childhood asthma?'*

2.3.1. Search Methods

Searches were performed on 8 September 2016 via the OvidSP search engine (http://ovidsp.ovid.com/). The following databases were selected and searched: Embase, Ovid MEDLINE (R) and Transport Database. Potentially relevant studies were identified using four sets of keyword combinations which identified the population, the exposure and the outcome of interest:

1. 'Child*' AND 'air pollution' AND 'asthma';
2. 'Child*' AND 'air quality' AND 'asthma';
3. 'Child*' AND 'vehicle emissions' AND 'asthma'; and
4. 'Child*' AND 'ultra-fine particles' AND 'asthma'.

Pilot searches and the literature review conducted prior to this study (Chapter 1 and previous M.Sc. dissertation) motivated the choice of these search terms. The term 'air pollution' captured the term 'traffic-related air pollution' in studies. The specific inclusion of the term 'ultra-fine particles' was because no observational study examining these pollutants' effects on asthma was encountered although toxicological evidence points to the pulmonary toxicity and relevance of ultra-fine particles in asthma pathogenesis (Li et al., 2003a, Chan et al., 2013, Oberdörster, 2000). No limits were applied on the initial publication date or language, in line with systematic review guidance (Tacconelli, 2010).

The reference lists of all included studies and of previous reviews on this topic were manually searched to identify any additional relevant studies (Anderson et al., 2013, Braback and Forsberg, 2009, Gasana et al., 2012, Gowers et al., 2012, Health Effects Institute, 2010, Salam et al., 2008, Sarnat and Holguin, 2007, Wong and Leung, 2005, Bowatte et al., 2015, Favarato et al., 2014). Authors of unpublished studies (abstracts only) and authors of the most recurrent studies were contacted to identify any additional relevant studies. This resulted in the inclusion of 2 extra studies that were not identified through the database searches (Yang et al., 2016, Kim et al., 2016). Finally, Google was searched for any other material related to 'traffic-related air pollution and childhood asthma' and 1 extra study was identified (Hasunuma et al., 2016). Studies were exported into an Endnote X7.4 library and duplicates automatically removed using the 'Find Duplicates' function.

2.3.2. Inclusion and Exclusion Criteria

The inclusion and exclusion criteria were devised around the review's question, as shown in Figure 2.

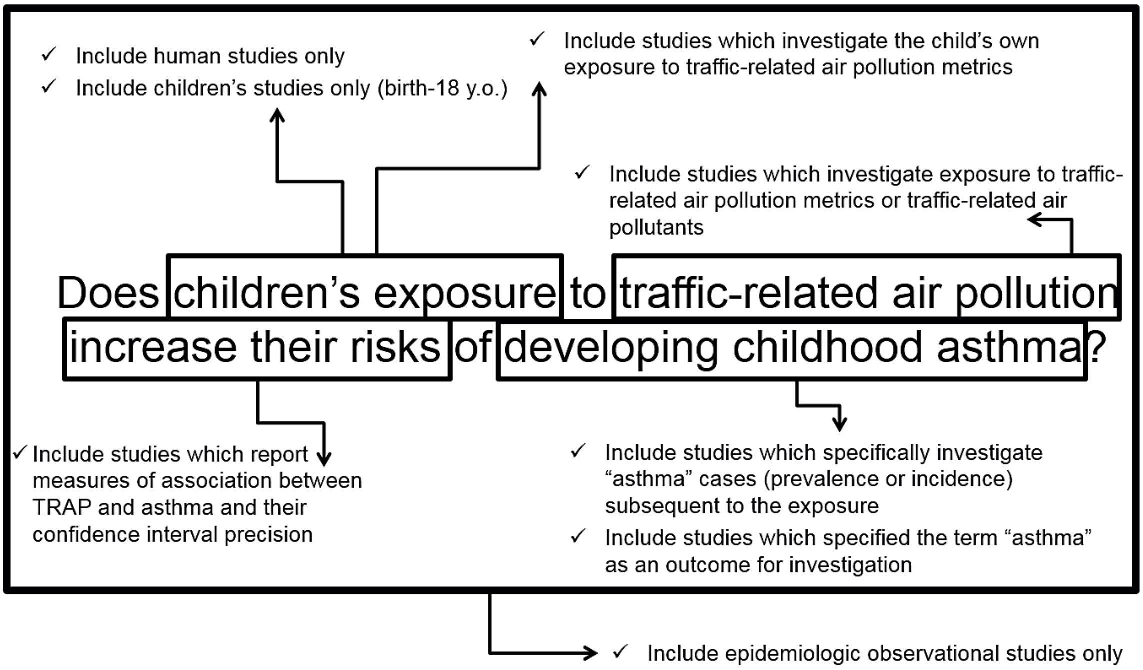


Figure 2 Elements of the Systematic Review Question for Inclusion and Exclusion Criteria Determination, Source: Own Work

For inclusion, studies which met all the following criteria were selected:

- were published epidemiological/observational studies including case-control, cohort and cross-sectional studies which can all offer evidence on risk factors for disease onset, if designed accordingly;
- explicitly specified the term 'asthma' as one outcome for investigation;
- examined childhood exposure from birth to 18 years old (World Health Organization, 2014) to any designated TRAP metric or established traffic-related air pollutants including carbon monoxide (CO), elemental carbon

(EC), nitrogen oxides (NO_x), nitric oxide (NO), nitrogen dioxide (NO_2), hydrocarbons, Particulate Matter equal or less than 2.5 micrometres in diameter ($PM_{2.5}$), Particulate Matter equal or less than 10 micrometres in diameter (PM_{10}), Particulate Matter between 2.5 and 10 micrometres in diameter (PM_{coarse}), ultra-fine particles or $PM_{2.5}$ absorbance as a marker for black carbon (BC) concentrations; referred to as BC thereafter (Vardoulakis et al., 2003, Krämer et al., 2009); and

- examined and reported associations (risk estimates) between preceding exposure to TRAP and subsequent risk of asthma, reported as incidence or lifetime prevalence from birth until 18 years old.

Asthma development was considered as new asthma in previously healthy children when reported between two or more follow-ups or over the lifetime of the child in birth cohort studies or cross-sectional studies. Likewise, the case-control studies included either looked at lifetime asthma as a measures of asthma development (i.e. like birth cohort studies) or excluded children with a history of asthma in the control groups (i.e. like cohort studies). In all instances, the exposure to TRAP had to precede the outcome to ensure the correct temporal sequence of events. For example, associations between birth year exposure and lifetime asthma prevalence in cross-sectional studies were considered as associations between TRAP exposure and asthma development and hence such studies were included. As such, studies that investigate asthma incidence and those that investigate asthma lifetime prevalence were included, similarly to previous formulation (Health Effects Institute, 2010).

Studies reporting pooled or multicentre analyses using standardized methods were also included. This decision was made in line with the calls for greater standardization of cohort methods (Anderson et al., 2013) and combined analyses of standardized data to obtain more accurate exposure-response estimates (Fuertes et al., 2015). Furthermore, some cohort- and outcome-specific associations included in these pooled or multicentre analyses had not been previously published in individual studies (Fuertes et al., 2015) and provided new information to this and previous syntheses. Cohort-specific associations were extracted from papers reporting pooled or multicentre analyses as if they were reporting on individual studies. Specific attention was given to whether these studies should be included in the meta-analysis to avoid duplication. All non-English-language papers including a Czech, French and a Russian paper were ultimately excluded due to translation difficulties (Vitnerova et al., 1999, Salameh et al., 2015, Veremchuk et al., 2014).

Studies which met any of the following criteria were excluded:

- were reviews, commentaries, governmental reports, letters, animal and experimental studies;
- only examined adulthood asthma;
- only examined non-traffic-related air pollutants or air pollution metrics including ozone (O_3), SO_2, indoor air pollution, proximity to point sources and wood smoke;
- only examined the association between the exposure to TRAP and asthma exacerbations, severity, or other allergic or respiratory diseases and symptoms;
- only examined the association between the exposure to any TRAP metric in utero and risk of subsequent asthma development. Such effects may be a result of the mother's exposure rather than the foetus (e.g. epigenetic changes) and warrant distinction; and
- only examined associations between concurrent exposure to TRAP and risk of asthma incidence or lifetime prevalence from birth until 18 years old.

2.3.3. Studies Screening and Selection

Titles and abstracts of all identified records were screened by the author. A random 20% were independently screened by another researcher (Charlotte Kelly). All potentially relevant studies were retrieved, and their full-papers reviewed against the inclusion criteria by the author. A random 50% were independently reviewed by another researcher (Mark Nieuwenhuijsen).

2.3.4. Data Extraction

Data was extracted by the author using a predefined data template which identified the key data items to be synthesized and analysed (Khreis et al., 2014). A random 20% was independently extracted by two other researchers (Charlotte Kelly and James Tate). Data was primarily extracted from the main papers of the included studies. Where necessary information was missing from the main papers, data was extracted from the supplementary materials and/or associated publications. Data extraction was undertaken manually.

2.3.5. Quality Assessment

Using the checklists and procedure provided in the Critical Appraisal Skills Programme (CASP) (Critical Appraisal Skills Programme, 2014), the validity of each included study was evaluated across six key parameters:

1. potential for selection bias;
2. outcome measurement or classification bias;
3. exposure measurement, recall or classification bias;
4. identification of and adjustment for important confounders;
5. length and completion of follow-up; and
6. any special characteristics that might compromise the generalizability of findings.

The CASP checklists are given in the form of 11 and 12 questions for cohort and case-control studies, respectively, and are designed to help the assessor think about the validity of each study. The questions are answered by a 'yes', 'no' and 'can't tell'. The cohort study checklist was used for cross-sectional studies, which did not have a specific checklist. All the included studies were independently evaluated by the author and another researcher (Mark Nieuwenhuijsen).

2.3.6. Meta-analysis

Random-effects meta-analyses were conducted to summarize the risk estimates (measures of associations between preceding exposure to TRAP and subsequent risk of asthma) across the range of included studies. Random-effects models were selected as they account for within study variance caused by chance and sampling error, but also for between studies variance caused by heterogeneity (Kirkwood and Sterne, 2003), a feature that is likely to exist in studies of TRAP exposures and asthma development (Health Effects Institute, 2010). All analyses were also performed using fixed-effect models as sensitivity analyses.

Figure 3 shows how studies and the risk estimates within were selected for inclusion in the meta-analysis. Meta-analyses were conducted by pollutant. Only studies that specifically measured or modelled the exposure to a traffic-related air pollutant and reported adjusted hazard ratios (HR), risk ratios (RR) and/or odds ratios (OR) for the risk of asthma per increment change in pollutant concentration were included. HH, RR and OR were all included in the same meta-analyses, following previous practice (Anderson et al., 2013) and being acceptable in the present situation where the outcome of interest is common whilst the effect size is small (Davies et al., 1998).

Although no guideline exists for the minimum number of studies needed to conduct a meta-analysis (Vrijheid et al., 2011), four risk estimates for a pollutant-outcome pair were considered as the minimum to justify running a meta-analysis and to enable running subsequent sensitivity analyses:

- excluding the study that contributed to the largest weight (the smallest standard error) to test the robustness of findings;
- excluding case-control and cross-sectional studies, where the potential for selection bias can be higher; and
- excluding studies with special characteristics that might compromise the generalizability of findings (e.g. high-risk birth cohorts).

Associations with five traffic-related air pollutants were reported in at least four studies. The adjusted risk estimates and their 95% CI were standardized into the following pollutant concentration increments to enable combining them in the meta-analyses:

- 0.5×10^{-5} m^{-1} BC;
- 4 $\mu g/m^3$ NO_2;
- 30 $\mu g/m^3$ NO_x;
- 1 $\mu g/m^3$ $PM_{2.5}$; and
- 2 $\mu g/m^3$ PM_{10}

The levels of BC and NO_x in ambient air are not legally regulated so the above increments were selected to approximately equal 10% of the maximum concentrations encountered in the included studies (maximum BC ≈ 6×10^{-5} m^{-1}, maximum NO_x ≈ 300 $\mu g/m^3$).

The remaining concentration increments represent 10% increments of the World Health Organization (WHO) Air Quality Guideline values (Krzyzanowski and Cohen, 2008). Where needed, the WHO conversion factor between parts per billion (ppb) and $\mu g/m^3$ for NO_2 was used to convert the concentration increments within studies into the same metric (1 ppb = 1.88 $\mu g/m^3$ NO_2) (Department for Environment Food and Rural Affairs, 2014a).

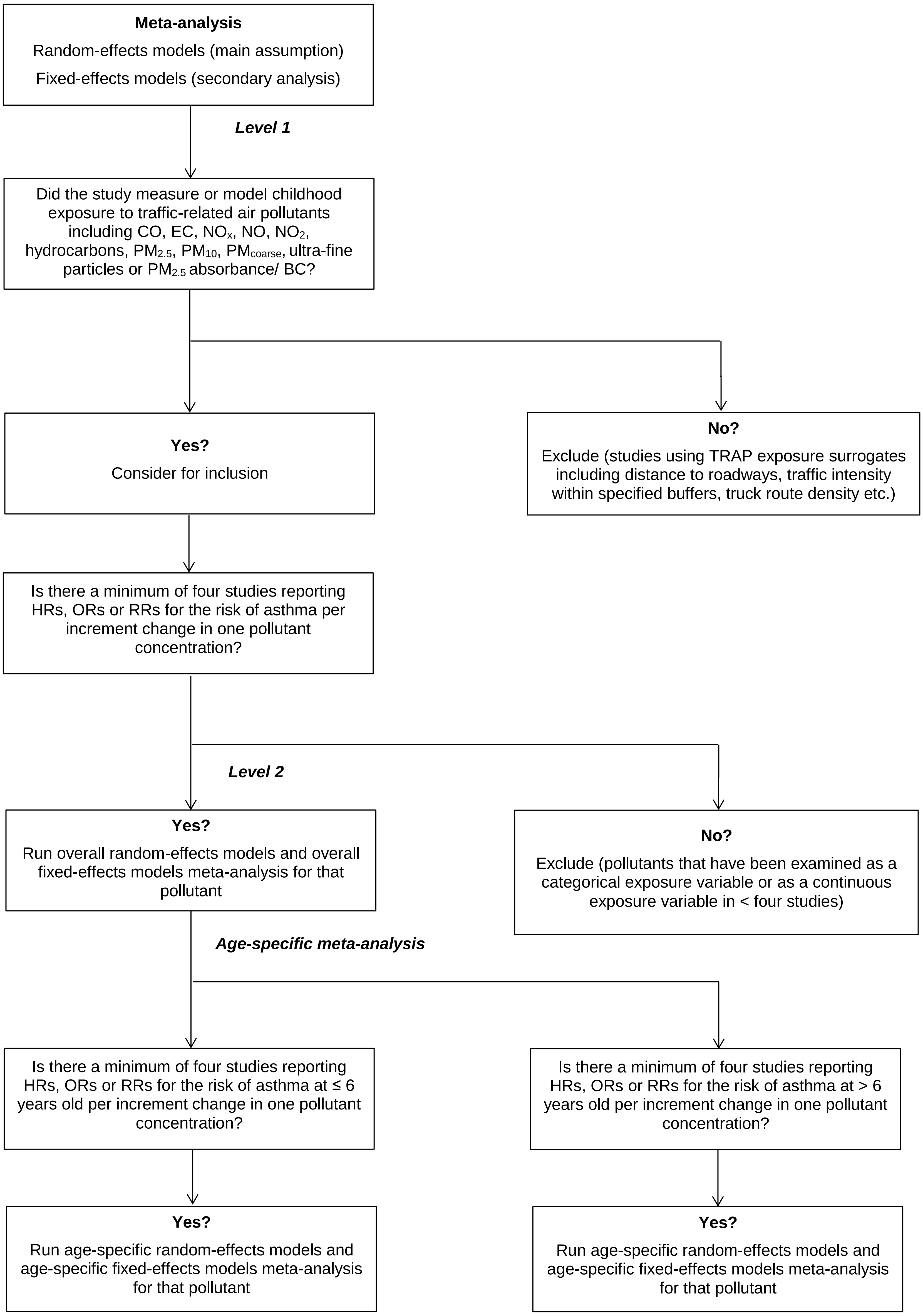


Figure 3 Study Selection Process for Meta-Analysis, Source: Own Work (Word)

Two series of meta-analyses were undertaken. The first series of meta-analyses, referred to as 'overall meta-analysis', pooled all available risk estimates for the associations between traffic-related air pollutants and asthma, without regard to age of onset. This approach is limited due to the broad age range at which risk estimates have been combined but was used to maximize statistical power to detect associations and heterogeneity. To ensure no study is double counted in the meta-analysis, a few selection criteria were applied to multiple publications using the same populations/cohorts, pooled analysis of multiple cohorts and publications with overlap between study populations. Where multiple publications used the same population (Brauer et al., 2007, Brauer et al., 2002, Fuertes et al., 2013, Gehring et al., 2010, Morgenstern et al., 2008, MacIntyre et al., 2014a, Gehring et al., 2015a, Deng et al., 2015, Deng et al., 2016), only the most recent publication was included (Fuertes et al., 2013, Gehring et al., 2010, Gehring et al., 2015a, Deng et al., 2016). In the case of studies reporting pooled analysis of multiple cohorts (Gehring et al., 2015b, MacIntyre et al., 2014a), when data from the specific cohort SAGE was not included in the most recent publication including the other cohorts (Gehring et al., 2015b), only that specific cohort's missing data were pulled out from the older publication (MacIntyre et al., 2014a) for inclusion in the meta-analysis. Likewise, in the pooled analysis by Mölter et al. (2014b), only data relating to the MAAS cohort were included in the meta-analysis, as data relating to the other 5 cohorts were included as extracted from a subsequent, more recent, publication by Gehring et al. (2015b). Finally, where there was a significant overlap between study populations of the same age range (Gehring et al., 2002, Morgenstern et al., 2007), only the largest study population was included (Morgenstern et al., 2007).

The second series of meta-analyses, referred to as 'age-specific meta-analysis', pooled all available risk estimates for associations between traffic-related air pollutants and asthma split into two age groups to examine age differences: 1) asthma at ≤ 6 years old (pre-school age) and 2) asthma > 6 years old (school age).

This cut-off age was used as there is consensus that asthma is more readily diagnosed after 'school age'. Where multiple publications used the same population within the same age group (Brauer et al., 2007, Brauer et al., 2002, Gehring et al., 2002, Morgenstern et al., 2007, Shima and Adachi, 2000, Shima et al., 2002), only the most recent publication was included (Brauer et al., 2007, Morgenstern et al., 2007, Shima et al., 2002).

Where more than one risk estimate per pollutant was reported in one study, a few selection criteria, as described next, were applied to ensure selecting the risk estimates which were most alike; most conservative, most reliable and those which related to the period hypothesized to be most relevant for asthma development:

- selecting the risk estimate which related to the earliest exposure window (e.g. birth address exposure versus current/time-varying/later address exposure) (Nishimura et al., 2013, Ranzi et al., 2014, Dell et al., 2014, Gruzieva et al., 2013, Gehring et al., 2015b, Mölter et al., 2014b, Tétreault et al., 2016, Krämer et al., 2009);
- selecting the risk estimate which was most inclusive in capturing asthma over the follow-up period (e.g. incidence over 2 years versus 1 year) or that which emerged from the most recent follow-up (Brauer et al., 2007, Gruzieva et al., 2013, Mölter et al., 2014b);
- selecting the risk estimate which related to the most restrictive asthma definition (e.g. ever having been diagnosed with asthma by a doctor accompanied with wheeze or use of asthma medication in the last 12 months versus ever having been diagnosed with asthma by a doctor) (Dell et al., 2014);
- selecting the risk estimate which related to the most restrictive analysis model (e.g. including adjustment for indoor environmental factors or indirect adjustment for smoking versus not including them) (Deng et al., 2016, Tétreault et al., 2016);
- selecting the risk estimate which related to the total population in the wider geographical area (versus smaller/disaggregated geographical areas) (Fuertes et al., 2013, Nishimura et al., 2013, Gehring et al., 2002, Morgenstern et al., 2008);
- selecting the risk estimate which related to the annual exposure (versus seasonal exposure) (Jerrett et al., 2008);
- selecting the risk estimate which was estimated using the exposure model with the higher spatial resolution (e.g. land-use regression models versus inverse-distance weighting) (Clark et al., 2010, Dell et al., 2014); and
- selecting the risk estimate which related to the total/summed exposures from traffic (versus separate freeway, non-freeway, home and school exposures) (McConnell et al., 2010).

The natural logarithm of each standardized risk estimate and its Standard Error (SE) were calculated and entered in RevMan version 5.3. (Copenhagen: The Nordic Cochrane Centre, The Cochrane Collaboration, 2014). Using the generic inverse variance method, each standardized risk estimate was weighted by the study's inverse variance in the fixed-effects models, whilst adjusting its SE to incorporate a measure of the extent of heterogeneity across studies in the random-effects models (Deeks et al., 2011).

For assessing heterogeneity, the I^2 statistic (Higgins et al., 2003) and the P-value from the Chi-squared test of heterogeneity were used. In line with established guidance, an I^2 value ≥ 50% was considered to suggest substantial heterogeneity and a P-value ≤ 0.1 was considered to suggest the presence of statistically significant heterogeneity (Deeks et al., 2011). Publication bias was visually examined with funnel plots using SE as the measure of study size (Sterne and Egger, 2001).

2.4. Results

2.4.1. Overview

The database searches yielded 4,276 unique articles and from this, 94 records were identified for full-text review (Figure 4). Forty-one studies, published between 1999 and September 2016, met the inclusion criteria. There was a recent growth in the number of studies on the topic with 18 out of the 41 studies (≈ 44%) emerging after the year 2014. A summary of each included study is provided in Table 1.

Ages of participants ranged from 1 to 18 years old, except in Nishimura et al. (2013) where 3% of the participants were 19-21 years old. This study was included as the substantial majority of participants fell within the pre-specified age range. Sample sizes ranged from 184 (Carlsten et al., 2010) to 1,133,938 children (Tétreault et al., 2016). Follow-up periods ranged from 1 to 16 years (Gehring et al., 2015b). Seventeen studies were conducted in Europe, 11 in North America, 5 in Japan, 3 in China and 1 in each of Korea and Taiwan. The remaining 3 articles reported on pooled analysis from multiple combined cohorts, mainly from Europe (Gehring et al., 2015b, MacIntyre et al., 2014a, Mölter et al., 2014b). These pooled studies used harmonized outcome definitions, exposure assessments and statistical methods as part of the Mechanisms of the Development of Allergy (MeDALL) (Bousquet et al., 2011), the Traffic, Asthma and Genetics Study (TAG) (MacIntyre et al., 2013) and the European

Study of Cohorts for Air Pollution Effects (ESCAPE) (European Study of Cohorts for Air Pollution Effects, 2014) consortiums.

Thirty-one studies were cohort studies (24 of which were birth cohorts), 6 studies were case-control studies (2 of which were nested in a birth cohort) and 4 studies were cross-sectional studies. In the 26 studies utilizing birth cohort data; new cases of asthma were assumed captured by study design. This assumption is in line with one biological paradigm that assumes children to be born asthma-free, and that with time, some will develop the condition because of exogenous and endogenous factors (Health Effects Institute, 2010). The 7 non-birth cohort studies made a distinction between incident asthma arising during the follow-up and latent asthma which might have only been triggered by TRAP. As such, studies conducted within the Southern California Children's Health Study by Jerrett et al. (2008) and McConnell et al. (2010) excluded children with a current, lifetime or missing/unknown history of asthma and wheeze at study entry. Children with a current or history of asthma at the baseline survey were also excluded from the respective asthma incidence analysis in the 5 Japanese studies included (Hasunuma et al., 2016, Shima and Adachi, 2000, Shima et al., 2003, Shima et al., 2002, Yamazaki et al., 2014). The 4 cross-sectional studies (Deng et al., 2015, Kim et al., 2016, Deng et al., 2016, Liu et al., 2016) were included as lifetime asthma diagnosis was the outcome measure used, in association with TRAP exposures predating the diagnosis. Finally, the 4 case-control studies which were not nested in birth cohorts were specifically designed to study incident asthma in healthy children at baseline in association with TRAP exposures predating the diagnosis (Dell et al., 2014, English et al., 1999, Nishimura et al., 2013, Zmirou et al., 2004).

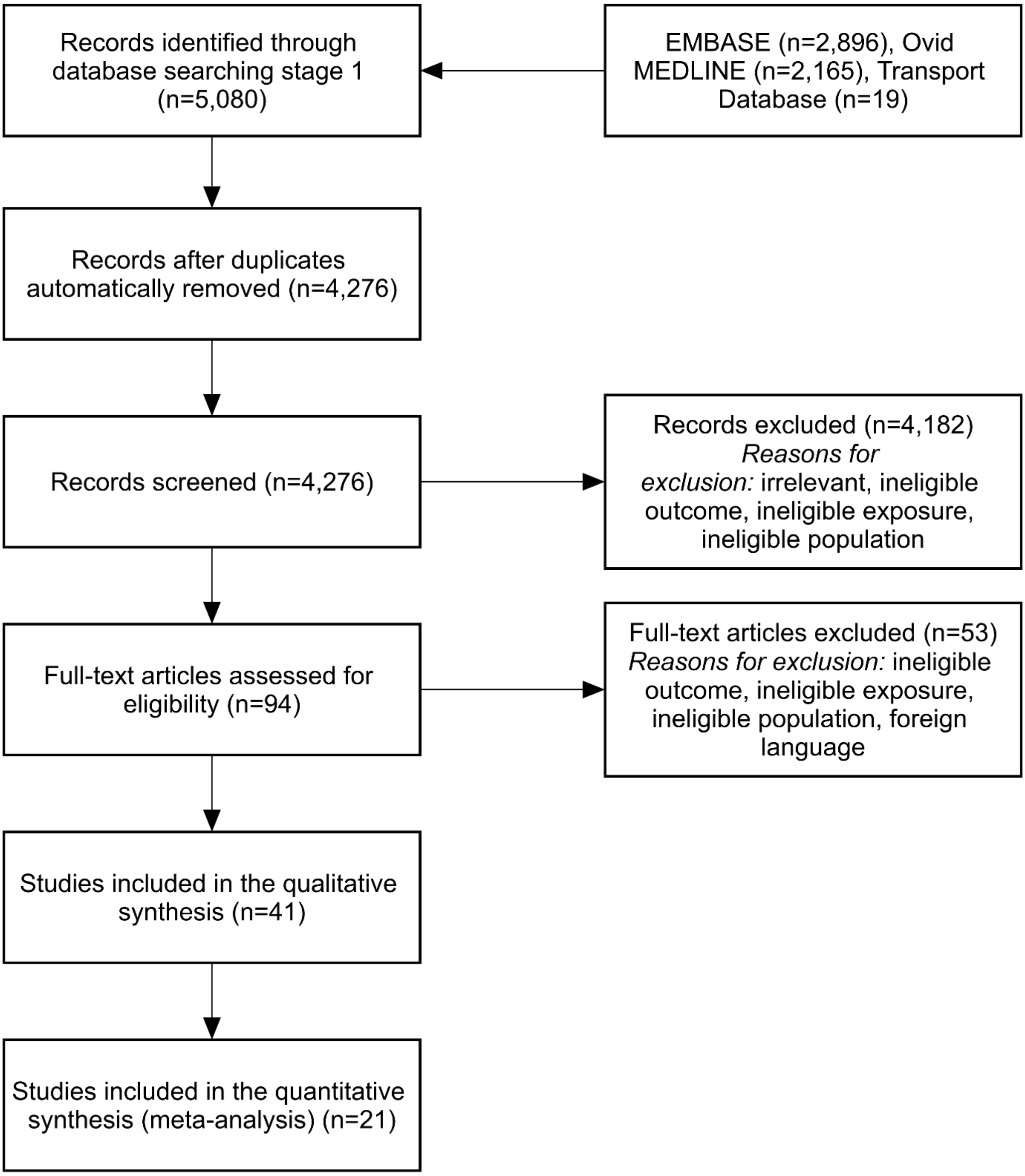


Figure 4 Flow Chart of Study Screening Process, Source: Own Work (NCH Software)

Table 1 Main Characteristics of Studies Included in the Systematic Review

Study reference and setting	Study design	Age group (years)	Participants included in the analysis	Exposure assessment	Pollutant(s)	Traffic-related exposures distribution	Asthma assessment and phenotypic characterization	Follow-up	Adjustment variables	CASP notes
Brauer et al. (2002), The Netherlands, north, west and centre communities	Birth cohort (PIAMA)	Birth-2	2,989	LUR modelling	BC, NO_2, $PM_{2.5}$	BC: range (0.77-3.68); mean (1.72) $10^{-5}m^{-1}$ NO_2: range (12.6-58.4); mean (25.6) µg/m^3 $PM_{2.5}$: range (13.5-25.2); mean (16.9) µg/m^3	Parental reporting of doctor-diagnosed asthma	@ 3 months, 1 and 2 y.o.	Mother smoking during pregnancy, smoking in home, study arm/mattress cover, mother education, father education, sex, gas stove, unvented gas water heater, siblings, ethnicity, breastfeeding at 3 months, any home mould, any home pets, allergies in mother, allergies in father, age of mother at child birth, region (in sensitivity analysis only)	Very young age for accurate diagnosis, follow-up duration is short, potential for recall bias in defining the outcome
Brauer et al. (2007), The Netherlands, north, west and centre communities	Follow-up on Brauer et al. (2002)	Birth-4	2,826	LUR modelling	BC, NO_2, $PM_{2.5}$	BC: range (0.77-3.68); mean (1.71) $10^{-5}m^{-1}$ NO_2: range (12.6-58.4); mean (25.2) µg/m^3 $PM_{2.5}$: range (13.5-25.2); mean (16.9) µg/m^3	Parental reporting of doctor-diagnosed asthma	@ 3 months, 1, 2, 3 and 4 y.o.	As in Brauer et al. (2002)	Young age for accurate diagnosis, follow-up duration is short, potential for recall bias in defining the outcome
Brunst et al. (2015), USA, Cincinnati	Birth cohort (CCAAPS)	Birth-7	589	LUR modelling	EC	EC: 75th percentile (0.45) µg/m^3 at birth; 75th percentile (0.39) µg/m^3 at age 7 y.o.	Asthma defined based on (1) asthma symptoms and bronchial hyper reactivity (>12% increase in FEV1 after bronchodilation) or a positive methacholine challenge test (>20% fall in baseline FEV1 at an inhaled methacholine concentration of <4 mg/ml) (2) parental reporting of doctor-diagnosis by a physician not associated with CCAAPS and, if so, at what age	@ 1, 2, 3, 4, and 7 y.o. and age of doctor diagnosis where applicable	Maternal education, parental history of asthma, day-care attendance, presence of a cat and/or dog in the home (race, sex, breastfeeding (< or >4 months), second-hand smoke exposure in 1st year of life, daily number of cigarettes smoked by household member > 0 were considered but not included in the final models)	High risk birth cohort[b], potential for recall bias in defining the outcome and selection bias, small (non-representative) sample size
Carlsten et al. (2010), Canada, Vancouver	Birth cohort (CAPPS)	Birth-7	184	LUR modelling	BC, NO, NO_2, $PM_{2.5}$	BC: mean (1.6) $10^{-5}m^{-1}$ NO: mean (35.7) µg/m^3	A single blinded paediatric allergist diagnosed asthma defined as ≥ 2 distinct episodes of 2+ weeks of cough, ≥ 2 distinct episodes of 1+ week of wheeze and one of the following: 1 weekly non-cold nocturnal cough, or	@ 7 y.o.	Maternal post-secondary education, mother/father/sibling asthma history, atopic status at 1 year, ethnicity, sex, intervention status	High risk birth cohort[b], no adjustment for smoking, small (non-representative) sample size

						NO_2: mean (32.6) µg/m^3 $PM_{2.5}$: mean (5.6) µg/m^3	hyperpnoea-induced cough/wheeze, or response to treatment with β-agonist and/or anti-inflammatories			
Clark et al. (2010), Canada, south-western British Columbia	Case-control nested in the British Columbia birth cohort	Birth-4	37,401	LUR modelling, monitoring data at closest three monitors weighted by inverse distance to child's residence, proximity to highways/ major roads	BC, CO, NO, NO_2, PM_{10}, $PM_{2.5}$	BC (LUR): mean (0.66 controls; 0.68 asthma cases) 10^{-5}m^{-1} CO: mean (605.0 controls; 617.5 asthma cases) µg/m^3 NO (LUR): mean (30.42 controls; 30.83 asthma cases) µg/m^3 NO_2 (LUR): mean (29.50 controls; 29.82 asthma cases) µg/m^3 PM_{10} (IDW): mean (12.37 controls; 12.42 asthma cases) µg/m^3 $PM_{2.5}$ (LUR): mean (4.50 controls; 4.59 asthma cases) µg/m^3	Asthma diagnosis identified from doctor billing records for primary care and hospital discharge records. Asthma defined as ≥ 2 primary care doctor diagnoses in a rolling 12-month period or ≥ 1 hospital admission for asthma using ICD-9 code 493	Mean age at end of follow-up: 4 years±7 months	Multiple births, age, sex, native status, breastfeeding, income quintile, education quartile, birth weight, gestational length (maternal age, maternal smoking and native status were considered but not included in the final models)	Young age for accurate diagnosis, excluding low birth weight /premature birth children may bias results towards the null, socioeconomic status variables assigned at the Census dissemination level, no adjustment for heredity
Fuertes et al. (2013), Germany	2 birth cohorts (GINIplus and LISAplus)	3-10	4,585	LUR modelling	BC, NO_2, $PM_{2.5}$	BC: range (1.0-3.6); mean (1.5) 10^{-5}m^{-1} NO_2: range (11.5-62.8); mean (22.4) µg/m^3 $PM_{2.5}$: range (0.4-21.5); mean (15.3) µg/m^3	Parental reporting of doctor-diagnosed asthma	GINIplus @ birth, 1, 2, 3, 4, 6 and 10 y.o., LISAplus @ birth, 0.5, 1, 1.5, 2, 4, 6 and 10 y.o.	Sex, age, older siblings, parental history of atopy, parental education, maternal smoking during pregnancy, smoke exposure in home, contact with furry pets during 1st year of life, use of gas stove during 1st year of life, home dampness/indoor moulds during 1st year of life, intervention participation, cohort and geographical area. Only children born	Participants differed from initial cohort, excluding children from the LISA with low birth weight /premature birth may bias results towards the null, potential for recall bias in defining the outcome

									at full-term and normal weight were recruited.	
Gehring et al. (2002), Germany, Munich	2 birth cohorts (GINI and LISA)	Birth-2	1,756	LUR modelling	BC, NO_2, $PM_{2.5}$	BC: range (1.38-4.39); mean (1.77) $10^{-5}m^{-1}$ NO_2: range (19.5-66.9); mean (27.8) µg/m^3 $PM_{2.5}$: range (11.9-21.9); mean (13.4) µg/m^3	Parental reporting of doctor-diagnosed asthmoid/ spastic/obstructive bronchitis	GINI @ birth, 1, and 2 y.o., LISA @ birth, 0.5, 1, 1.5, and 2 y.o.	Sex, parental atopy, tobacco smoke at home, maternal education, siblings, use of gas for cooking, home dampness, indoor mould, pets keeping and study arm	Very young age for accurate diagnosis, follow-up duration is short, excluding children from the LISA with low birth weight /premature birth may bias results towards the null, potential for recall bias in defining the outcome
Gehring et al. (2010), The Netherlands, north, west and centre communities	Follow-up on Brauer et al. (2007)	Birth-8	3,143	LUR modelling	BC, NO_2, $PM_{2.5}$	BC: range (0.77-3.68); mean (1.72) $10^{-5}m^{-1}$ NO_2: range (12.6-58.4); mean (25.2) µg/m^3 $PM_{2.5}$: range (13.5-25.2); mean (16.9) µg/m^3	Parental reporting of doctor-diagnosed asthma. Asthma categorized in 1,499 children at 8 years of age to atopic and non-atopic based on blood IgE concentrations to inhalant or food allergens	@ birth, 1, 2, 3, 4, 5, 6, 7 and 8 y.o.	As in Brauer et al. (2007) plus day-care attendance	Potential for recall bias in defining the outcome
Gehring et al. (2015a), The Netherlands, north, west and centre communities	Follow-up on Gehring et al. (2010)	Birth-12	3,702	LUR modelling	BC, NO_2, $PM_{2.5}$, PM_{10}, PM_{coarse} and PM composition elements: copper (Cu), iron (Fe), zinc (Zn), nickel (Ni), sulphur (S), vanadium (V)	BC: range (0.8-3.0); mean (1.2) $10^{-5}m^{-1}$ NO_2: range (9.2-59.6); mean (23.1) µg/m^3 $PM_{2.5}$: range (15.3-21.1); mean (16.4) µg/m^3 PM_{10}: range (23.7-33.2); mean (24.9) µg/m^3 PM_{coarse}: range (7.6- 14.0); mean (8.4) µg/m^3 For PM elemental composition	Parental reporting of doctor-diagnosed asthma	@ birth, 1, 2, 3, 4, 5, 6, 7, 8 and 11-12 y.o.	As in Gehring et al. (2010) plus birth weight in sensitivity analysis	Participants more likely to have highly educated parents and live in non-smoking homes

						elements; see table 2 in original paper				
Gehring et al. (2015b), Sweden, Germany, The Netherlands	Pooled data from four birth cohorts: BAMSE; GINIplus; LISAplus and PIAMA	Birth-16	14,126	LUR modelling	BC, NO_2, $PM_{2.5}$, PM_{10}, PM_{coarse}	BC at birth: BAMSE - range (0.4-1.3); mean (0.7) $10^{-5}m^{-1}$ GINI/LISA North - range (1.0-3.1); mean (1.2) $10^{-5}m^{-1}$ GINI/LISA South - range (1.3-3.6); mean (1.7) $10^{-5}m^{-1}$ PIAMA - range (0.8-1.2); mean (1.2) $10^{-5}m^{-1}$ NO_2 at birth: BAMSE - range (6.0-33.0); mean (14.1) µg/m^3 GINI/LISA North - range (19.7-62.8); mean (23.8) µg/m^3 GINI/LISA South - range (11.5-61.1); mean (21.8) µg/m^3 PIAMA - range (8.7- 59.6); mean (23.2) µg/m^3 $PM_{2.5}$ at birth: BAMSE - range (4.2-11.4); mean (7.8) µg/m^3 GINI/LISA North - range (15.8-21.5); mean (17.4) µg/m^3 GINI/LISA South - range (10.6-18.3); mean (13.4) µg/m^3 PIAMA - range (15.3-21.1); mean (16.4) µg/m^3 PM_{10} at birth: BAMSE - range (6.0-30.9); mean (15.7) µg/m^3	Asthma defined as a positive answer to at least two of the three questions: (1) "Has a doctor ever diagnosed asthma in your child?" (2) "Has your child had wheezing or whistling in the chest in the last 12 months?" and (3) "Has your child been prescribed asthma medication during the last 12 months?" Asthma categorized to allergic and non-allergic based on blood IgE concentrations against common aeroallergens	@ 1, 2, 4, 6–8, 10–12 and 14–16 y.o.	Sex, parental socioeconomic status, parental education, native nationality, maternal and paternal asthma or hay fever, older siblings, breastfeeding for at least 3 months, maternal smoking during pregnancy, parental smoking at home, mould or dampness, and furry pets in the child's home, use of natural gas for cooking, attendance at day-care centres, municipality (BAMSE only)	Does not account for long-term trends in TRAP levels, potential for selection bias as children of atopic and highly educated parents were over-represented, potential for recall bias in defining the outcome

						GINI/LISA North - range (23.9-33.9); mean (25.5) µg/m³ GINI/LISA South - range (14.8-34.4); mean (20.4) µg/m³ GINI/LISA South - range (23.7- 33.2); mean (25.0) µg/m³ PM_{coarse} at birth: BAMSE - range (0.7- 20.2); mean (7.9) µg/m³GINI/LISA North - range (1.9-13.9); mean (8·5) µg/m³ GINI/LISA South - range (4.1- 16.0); mean (6.8) µg/m³ PIAMA - range (7.6- 14.0); mean (8.4) µg/m³				
Gruzieva et al. (2013), Sweden, Stockholm	Birth cohort (BAMSE)	Birth-12	3,633	Dispersion modelling (Airviro, street canyon contribution for 160 houses) NO_x, PM_{10}	NO_x, PM_{10}	NO_x: mean (21.4) µg/m³ - above regional background (= 3 µg/m³) $PM_{10:}$ mean (4.2) µg/m³ - above regional background (= 10 µg/m³)	At 1 and 2 y.o., asthma defined as ≥ 3 episodes of wheeze and treatment with inhaled corticosteroids or signs of bronchial hyper reactivity without concomitant respiratory infection. At 4, 8 and 12 y.o., asthma defined as ≥ 4 episodes of wheeze in last year, ≥ 1 episode and prescription of inhaled corticosteroids. Asthma was categorized at 4 or 8 y.o. to atopic and non-atopic based on blood IgE concentrations to inhalant allergens	@ 1, 2, 4, 8 and 12 y.o.	Municipality, socioeconomic status, heredity, year the house was built	No adjustment for smoking, PM_{10} model calculations were performed only for year 2004 and assumed constant for all years during the study period (1994 to 2008), potential for recall bias in defining the outcome
Jerrett et al. (2008), USA, 11 southern Californian communities	Cohort (CHS)	10-18	209	NO_2 Palmes tubes monitoring for 2 weeks in 2 seasons at child's residence	NO_2	NO_2: annual mean in the 11 communities ranging from 9.6 ppb (at Lompoc) to 51.3 ppb (at San Dimas)	Parental and self-reporting of doctor-diagnosed asthma	@ 10, 11, 12, 13, 14, 15, 16, 17 and 18 y.o.	Age, sex, relative humidity, ethnicity, enrolment group, medical insurance coverage, enrolment group (body mass index, wheeze and symptoms of hay fever, medical care and socioeconomic status, parental education, mildew in home, carpet in bedroom, plants and pets in home, gas stove in	Small sample size, potential for recall bias in defining the outcome

									home, current daily smoker in home, maternal smoking during pregnancy, parental history of asthma considered but not included in the final models)	
Kerkhof et al. (2010), The Netherlands, north, west and centre communities	Birth cohort (PIAMA)	Birth-8	916	LUR modelling	BC, NO_2, $PM_{2.5}$	BC: median (1.77); interquartile range (1.30-1.91) $10^{-5}m^{-1}$ NO_2: median (25.8); interquartile range (17.4-28.6) µg/m^3 $PM_{2.5}$: median (17.2); interquartile range (14.7-18.1) µg/m^3	Two definitions: (1) parental reporting of doctor-diagnosed asthma (2) at least one attack of wheeze or dyspnoea and/or the prescription of inhaled corticosteroids in the last 12 months from age 2 up to age 8	@ birth, 1, 2, 3, 4, 5, 6, 7 and 8 y.o.	Sex, type of intervention (mite-impermeable mattress covers, placebo covers or no intervention), allergies of mother and father, parental education (low, intermediate or high), maternal smoking during pregnancy, exposure to smoke at home in the first year of life, duration of breastfeeding (never, 1e12 weeks, >12 weeks), presence of a gas stove, presence of older siblings, day-care attendance, signs of dampness in the house, presence of cats and/or dogs, type of home (single family dwelling ,apartment/flat) and presence of fitted carpeting	Small sample size, potential for selection bias, potential for recall bias in defining the outcome
Krämer et al. (2009), Germany, Wesel	2 birth cohorts (GINIplus and LISAplus)	4-6	2,059	LUR modelling, distance to next major road traversed by more than 10,000 cars/ day	BC, NO_2	BC: range (0.8-2.3); mean (1.6) $10^{-5}m^{-1}$ NO_2: range (13.6-41.4); mean (24.0) µg/m^3	Parental reporting of doctor-diagnosed asthma	GINI @ birth, 1, 2, 3, 4 and 6 y.o., LISA @ birth, 0.5, 1, 1.5, 2, 4 and 6 y.o.	Study arm, sex, years of parental schooling, maternal smoking in pregnancy, tobacco smoke, use of gas for cooking, contact with dog, cat, other furry pets, home mould and dampness, biological siblings, participant of intervention, intervention formulas, living on a farm, parental asthma, hay fever or eczema	Study in rural and small-town areas, participants differed than non-participants, potential for recall bias in defining the outcome
LeMasters et al. (2015), USA, Cincinnati	Birth cohort (CCAAPS)	Birth-7	575	LUR modelling	EC	EC: 75th percentile (0.42) µg/m^3 26.4% of normal BMI children and 27.5% of high BMI children were at ≥ 0.42 µg/m^3	Children were doctor diagnosed as asthmatic with symptoms of asthma and evidence of bronchial hyper-reactivity or a positive methacholine challenge test	@ 1, 2, 3, 4 and 7 y.o.	Sex, smoking in home, ethnicity, mother's education, breastfeeding, dog and/or cat in home during 1st year of life, attendance at day care during 1st year of life, stratification by BMI	High risk birth cohort[b], potential for recall bias of residential history and household smoking history

						73.7% of normal BMI children and 72.5% of high BMI children were at < 0.42 µg/m^3				
Lindgren et al. (2013), Sweden, Scania	Birth cohort	Birth-6	6,007	Dispersion modelling (AERMOD), traffic intensity on road with heaviest traffic within 100m around residence	NO_x	NO_x: range (6.1-45.9); mean (17.0) µg/m^3 73.8% living at ≤ 100 m from 0–8640 cars/day and 26.6% living at ≤ 100 m from ≥ 8640 cars/day	Asthma onset defined as incidence of 1st ever and 3rd year dispensed inhaled β2-agonist and corticosteroid	Children followed from birth (2005-2010) until 2011 (maximum= 6 y.o.)	Sex, tobacco smoke, breastfeeding, parental allergy, parental origin, parental education, birth year (birth weight, smoking during pregnancy, home mould, furred pets at home, problems to pay bills, type of housing considered but not included in the final models)	Potential for selection bias, crude traffic intensity categorization
MacIntyre et al. (2014a), Sweden, Canada, Germany, The Netherlands	Pooled data from 6 birth cohorts: BAMSE; CAPPS; GINI; LISA; PIAMA; SAGE	Birth-8	5,115	LUR modelling, dispersion modelling for BAMSE only	NO_2 (sensitivity analyses for BC and $PM_{2.5}$)	NO_2: pooled data - range (2.2-66.8); mean (22.7) µg/m^3	Parental reporting of doctor-diagnosed asthma. CAPPS and SAGE children were also evaluated by a paediatric allergist to confirm asthma	Children followed at different time points depending on the cohort	Study, city, sex, birth weight, parental history of allergy, maternal age at birth, maternal smoking reported anytime during pregnancy, environmental tobacco smoke reported in the home, and intervention, stratification by genotype	No adjustment for socioeconomic status, potential for selection bias, potential for recall bias in defining the outcome
McConnell et al. (2010), USA, 13 southern Californian communities	Cohort (CHS)	Kindergarten/1st grade - 4th grade	2,497	Dispersion modelling for NOx (CALINE 4), monitoring data for NO_2, $PM_{2.5}$, PM_{10}, distance to nearest freeway or other highways or arterial roads, traffic density within 150m around residence and school	NO_x, NO_2, $PM_{2.5}$, PM_{10}	NO_x: total at residence - range (0.23-144.1); mean (18.4) ppb NO_2: range (8.7-32.3); mean (20.4) ppb $PM_{2.5}$: range (6.3-23.7); mean (13.9) µg/m^3 PM_{10}: range (17.6-61.5); mean (35.5) µg/m^3 Traffic density: at residence - range (<0.0001-1,029); mean (48.3) Distance to freeway: at residence - range	Self-reporting of doctor-diagnosed asthma	Annual questionnaires during 3 years' follow-up	Age, sex, ethnicity (history of allergy, play team sport, parental history of asthma, maternal smoking during pregnancy, second-hand smoke, mildew, pets in home, indoor NO_2 sources, wildfire exposure, health insurance, household income and parental education were considered but not included in the final models)	Potential for recall bias in defining the outcome, potential for selection bias

						(24-18,210); mean (1,912) m Distance to major road: at residence - range (0.02-7,516); mean (433) m				
Mölter et al. (2014a), England, Greater Manchester	Birth cohort (MAAS)	Birth-11	1,108	Micro environmental exposure model (LUR modelling for outdoor and INDAIR for indoor environments, indoor to outdoor ratios: journey to school and school)	NO_2, PM_{10}	NO_2: birth year - mean (21.7) μg/m^3 PM_{10}: birth year - mean (12.8) μg/m^3	Asthma defined as at least two positive answers to the following three questions: (1) doctor-diagnosis of asthma ever; (2) child having wheezed during the previous 12 months and (3) child having received asthma medication during the previous 12 months	@ 3, 5, 8, and 11 y.o.	Age, sex, body mass index, paternal income at birth, sensitization, family history of asthma, hospitalization during the first 2 years of life, smoking within the child's home during the first year of life, and Tanner stage (age 11 only) (ethnicity, older siblings, parental atopy, day care attendance, presence of a gas cooker in the home, visible signs of dampness or mould in the home, presence of a dog or a cat in the home, birth weight, gestational age, maternal age at birth, and duration of breastfeeding were considered but not included in the final models)	Limited number of children with a full set of exposure estimates available for follow-up, more restrictive asthma definition, potential for recall bias as review of microenvironments only done at age 11, potential for recall bias in defining the outcome
Mölter et al. (2014b), England, Sweden, Germany, The Netherlands	Pooled data from 5 birth cohorts: MAAS, BAMSE, PIAMA, GINI, LISA (South and North)	Birth-10	10,377	LUR modelling, traffic intensity on the nearest street, traffic intensity on major roads within a 100m radius	BC, NO_2, NO_x, $PM_{2.5}$, PM_{10}, PM_{coarse}	BC at birth: MAAS - range (0.7-2.0); mean (1.2) $10^{-5}m^{-1}$ BAMSE - range (0.4-1.3); mean (0.7) $10^{-5}m^{-1}$ PIAMA - range (0.9-3.0); mean (1.2) $10^{-5}m^{-1}$ GINI/LISA South - range (1.3-3.6); mean (1.7) $10^{-5}m^{-1}$ GINI/LISA North - range (0.9-3.1); mean (1.2) $10^{-5}m^{-1}$ NO_2 at birth: MAAS - range (16.0-30.4); mean (22.9) μg/m^3	Asthma defined as at least two positive answers to the following three questions: (1) doctor-diagnosis of asthma ever; (2) child having wheezed or whistled during the previous 12 months and (3) child having received asthma medication during the previous 12 months	@ 4 (age 5 in MAAS), and 8 y.o. (age 10 in GINI/LISA)	Age, sex, older siblings, gas cooking, dampness or mould, maternal smoking during pregnancy, any smoker living in the home, >12 weeks of breastfeeding, day-care attendance, parental atopy, personal socioeconomic status, maternal age at birth, presence of a dog in the home, presence of a cat in the home, region, area-level socioeconomic status, birth weight, moving status (sensitivity analysis)	Potential for misclassification of personal exposure, more restrictive asthma definitions, potential for recall bias in defining the outcome

BAMSE - range (6.0-33.0); mean (14.0) µg/m^3

PIAMA - range (9.2-55.3); mean (23.2) µg/m^3

GINI/LISA South - range (11.5-61.1); mean (22.0) µg/m^3

GINI/LISA North - range (19.6-62.8); mean (23.9) µg/m^3

$PM_{2.5}$ at birth: MAAS - range (9.4-11.0); mean (9.4) µg/m^3

BAMSE - range (4.2-11.4); mean (7.8) µg/m^3

PIAMA - range (15.3-20.9); mean (16.4) µg/m^3

GINI/LISA South - range (10.6-18.3); mean (13.4) µg/m^3

GINI/LISA North - range (15.8-21.5); mean (17.4) µg/m^3

PM_{10} at birth: MAAS - range (12.6-22.7); mean (17.2) µg/m^3

BAMSE - range (6.0-30.9); mean (15.7) µg/m^3

PIAMA - range (23.7-32.7); mean (25.0) µg/m^3

GINI/LISA South - range (14.8-34.3); mean (20.4) µg/m^3

GINI/LISA North - range (23.9-33.5); mean (25.5) µg/m^3

PM_{coarse} at birth: MAAS - range (5.0-

						11.5); mean (7.0) µg/m^3 BAMSE - range (0.7-20.2); mean (7.9) µg/m^3 PIAMA - range (7.6-11.1); mean (8.4) µg/m^3 GINI/LISA South - range (4.1-16.0); mean (6.8) µg/m^3 GINI/LISA North - range (2.0-13.8); mean (8.5) µg/m^3				
Morgenstern et al. (2007), Germany, Munich Metropolitan area	2 birth cohorts (GINI and LISA) – extension on Gehring et al. (2002)	Birth-2	3,577	LUR modelling, living close to major road	BC, NO_2, $PM_{2.5}$	BC: range (1.3-3.2); mean (1.7) $10^{-5}m^{-1}$ NO_2: range (19.4-71.7); mean (35.3) µg/m^3 $PM_{2.5}$: range (6.8-15.3); mean (12.8) µg/m^3	Parental reporting of doctor-diagnosed asthmoid/ spastic/obstructive bronchitis	GINI @ birth, 1, and 2 y.o., LISA @ birth, 0.5, 1, 1.5, and 2 y.o.	Sex, age, parental atopy, tobacco smoke at home, maternal education, siblings, use of gas for cooking, home dampness, indoor mould, dogs and cats keeping	Very young age for accurate diagnosis, follow-up duration is short, potential for recall bias in defining the outcome
Morgenstern et al. (2008), Germany, Munich	2 birth cohorts (GINI and LISA)	4-6	2,436	LUR modelling, minimum distance to next motorway, federal or state road	BC, NO_2, $PM_{2.5}$	BC at 2/3 y.o.: range (1.1-3.3); mean (1.7) $10^{-5}m^{-1}$ NO_2 at 2/3 y.o.: range (8.0-58.4); mean (34.7) µg/m^3 $PM_{2.5}$ at 2/3 y.o.: range (1.3-15.0); mean (11.1) µg/m^3	Parental reporting of doctor-diagnosis of asthmatic/spastic/obstructive bronchitis or asthma	GINI @ birth, 1, 2, 3, 4 and 6 y.o., LISA @ birth, 0.5, 1, 1.5, 2, 4 and 6 y.o.	Sex, age, parental atopy, maternal education, siblings, tobacco smoke at home, use of gas for cooking, home dampness, indoor moulds, dogs and cats keeping	Potential for recall bias in defining the outcome
Oftedal et al. (2009), Norway, Oslo	Oslo birth cohort and sample from simultaneous cross-sectional study	Birth-10	2,329	Dispersion modelling (EPISODE), distance to main transport routes with any form of motor transport	NO_2	NO_2 at birth year: range (1.5-84.0); mean (39.3) µg/m^3	Parental reporting of doctor-diagnosed asthma	Questionnaires completed at baseline and at 10 y.o. with a question about age of first diagnosis	Sex, parental atopy, maternal smoking in pregnancy, paternal education, maternal marital status at the child's birth, contextual neighbourhood level socioeconomic factors cohort indicator, keeping furry pets now, dampness problems now, parental ethnicity (age, birth weight, furry pets in early life, wall to wall carpeting in early life, dampness	Potential for selection bias and recall bias in defining the outcome and diagnosis age, no adjustment for second-hand smoking

									problems in early life, parental ethnicity and maternal education considered but not included in the final model)	
Patel et al. (2011), USA, New York	Birth cohort (CCCEH)	Birth-5	593	Proximity to roadways, roadway density, truck route density, four-way street intersection density, number of bus stops, percentage of building area designated for commercial use	NA	At prenatal address (following addresses only reported as change in reference to prenatal address) Proximity to roadways: range (0.01-3.8); median (0.44) km Roadway density: range (10.9-45.5); median (19.4) km roadways/km^2 land Truck route density: range (0-12.6); median (2.5) km truck routes/km^2 land Four-way street intersection density: range (0-107); median (45.9) (# intersections/km^2 land Number of bus stops: range (0-17); median (6) stops Percentage of commercial building area: range (0.55-56.8); median (6.2)	Parental reporting of doctor-diagnosed asthma	Questionnaires completed every 3 months between birth and 2 y.o. and every 6 months from 2 y.o. to 5 y.o.	Sex, age, ethnicity, presence of smokers in the home, annual household income, concentrations of German cockroach and mouse allergen in dust samples	Study of Dominicans and African Americans, subjects included in analysis had lower asthma proportions than fully enrolled cohort, no adjustment for heredity, potential for recall bias in defining the outcome
Ranzi et al. (2014), Italy, Rome	Birth cohort (GASPII)	Birth-7	672	LUR modelling, proximity to high traffic roads	NO_2	NO_2 at birth year: range (15.2-59.58); mean (37.17) µg/m^3	Maternal reporting of doctor-diagnosed asthma	@ 6, 15 months, 4 and 7 y.o.	Sex, age, breastfeeding at 3 months, day care attendance, presence of pets in home, siblings, maternal and paternal	Potential for selection bias and recall bias in defining the outcome

						Proximity to high traffic roads at baseline: range (1.00- 10054.78); mean (395.12) m			smoking, maternal smoking during pregnancy, maternal and paternal education, presence of mould or dampness at home, familial asthma/allergies	
Shima and Adachi (2000), Japan, 7 Chiba Prefecture communities	Cohort	9/10-12/13	842	Monitoring data	NO_2	NO_2: annual mean in the 7 communities ranging from 7.0 ppb (at Tateyama) to 31.3 ppb (at Ichikawa)	Parental reporting of asthma defined as ≥ 2 episodes of wheezing accompanied by dyspnoea that had ever been given the diagnosis of asthma by a doctor and occurrence of attacks or need for medication in past 2 years	Annual questionnaires during 3 years' follow-up	Sex, history of allergic disease, early-life respiratory diseases, breastfeeding in infancy, parental history of allergic disease, parental smoking habits, indoor NO_2, use of unvented heater in winter	Non-participants higher in urban districts, no adjustment for socioeconomic status, potential for recall bias in defining the outcome
Shima et al. (2002), Japan, 8 Chiba Prefecture communities	Cohort	6-12	1,910	Monitoring data	NO_2, PM_{10}	NO_2: annual mean in the 8 communities ranging from 7.3 ppb (at Tateyama) to 31.4 ppb (at Ichikawa) PM_{10}: annual mean in the 8 communities ranging from 27.9 µg/m^3 (at Tateyama) to 53.7 µg/m^3 (at Chiba)	As in Shima and Adachi (2000)	Annual questionnaires during 6 years' follow-up	City, sex, history of allergic disease, early-life respiratory diseases, parental history of allergic diseases, maternal smoking habits, use of unvented heater in winter, house of steel/reinforced concrete	Non-participants higher in urban districts, no adjustment for socioeconomic status, potential for recall bias in defining the outcome
Shima et al. (2003), Japan, 8 Chiba Prefecture communities	Cohort	6/9-10/13	1,858	Distance to trunk roads	NA	Traffic density range (33,775-83,097) vehicles/12 hours	As in Shima and Adachi (2000)	Annual questionnaires during 4 years' follow-up	Sex, school grade, history of allergic diseases, early-life respiratory diseases, breastfeeding in infancy, parental history of allergic diseases, maternal smoking, house of steel/reinforced concrete, use of unvented heater in winter	Non-participants higher in urban districts, no adjustment for socioeconomic status, potential for recall bias in defining the outcome
Tétreault et al. (2016), Canada, Québec	Birth cohort	Birth-12	1,133,938	LUR modelling for NO_2, satellite imagery for $PM_{2.5}$	NO_2, $PM_{2.5}$	NO_2 at birth: range (4.47, 35.90); mean (15.51) ppb $PM_{2.5}$ at birth: range (2.32, 14.85); mean (9.86) µg/m^3	Any hospital discharge showing a diagnosis of asthma (in any diagnostic field) or two physician claims for asthma (visits to the emergency room or physician's office) occurring within a 2-year period (indexing occurred on the second visit)	NA	Sex, quintiles of the Pampalon deprivation index, year of birth in the cohort, second-hand smoke, region	Socioeconomic status was not available on individual base and was assessed using an area wide variable, adjustment for second-hand smoke was indirect, $PM_{2.5}$ calculations were performed at a large scale and only for years 2001 to 2006 and assumed constant for all years during the

										study period (1996 to 2011), no adjustment for heredity
Wang et al. (2016c), Taiwan, 11 communities in Taipei	Cohort (CEAS)	Birth-kindergarten (average age 5.5 ± 1.1)	2,661	Monitoring data	CO, NO_2, $PM_{2.5}$, PM_{10}	CO: range (0.39, 0.82); mean (0.63) ppb NO_2: range (16.48, 26.03); mean (23.04) ppb $PM_{2.5}$: range (17.55, 30.45); mean (28.81) µg/m^3 PM_{10}: range (27.75, 52.77); mean (48.14) µg/m^3	Doctor-diagnosed asthma and the presence of nocturnal cough or exercise wheeze in the past 12 months	At average age 5.5 ± 1.1	Sex, age, body mass index, environmental tobacco smoke, maternal history of atopy, maternal education and nationality, duration of breastfeeding, duration of sleep, number of siblings, temperature, relative humidity, and distance from home to the monitoring station (family income, dampness in the house, fungus on the house walls considered but not included in the final models)	Excluding premature birth children may bias results towards the null, potential for selection bias, potential for exposure misclassification (children's residences within 10 km from the air monitoring stations), potential for recall bias in defining the outcome
Yamazaki et al. (2014), Japan, 57 elementary schools	Cohort (SORA)	6-9	10,069	Dispersion modelling for outdoor and indoor concentrations, living near heavily trafficked roads	EC, NO_x	EC: 814 children at highest EC level (≤ 2.2 µg/m^3) and 892 children at lowest EC level (≥ 3.3 µg/m^3) NO_x: 997 children at highest NO_x level (≤ 38.9 ppb) and 978 children at lowest NO_x level (≥ 57.4 ppb) Living near heavily trafficked roads: 794 children at < 50 m zone; 7726 children at ≥ 50 m zone; 1549 children at reference area	Asthma defined based on "yes" answers to all of the following five questions: "has your child ever had an attack of wheezing or whistling that has caused him/her to be short of breath?", "has he/she ever had 2 or more such episodes?", "has a doctor ever said that he/she had asthma, asthmatic bronchitis, or child asthma?", "on that occasion, did his/her chest sound wheezy or produce a whistling sound?", and "at that time, did he/she have difficulty in breathing, accompanied by wheezing or whistling?"	Follow-up surveys were conducted annually for 4 years after baseline survey	Sex, grade as a surrogate variable of age, body mass index, respiratory symptoms, presence of allergic disease, feeding during the lactation period, past history of diseases or surgery, smoker in the household, siblings and first-born child, parents' past history of respiratory illnesses, housing materials, cookware used at home, heating system installed, humidifier/dehumidifier use, presence of mould in house, flooring materials used, presence of pets, use of air cleaners, use of clothes dryers, background concentrations of air pollution, and area	Restrictive asthma definition, decreasing concentration of air pollutants over the study period could have caused the ORs to be overestimated, potential for recall bias in defining the outcome, no adjustment for socioeconomic status
Yang et al. (2016), The Netherlands, north, west and centre communities	Birth cohort (PIAMA)	Birth-14	3,701	LUR modelling	Oxidative Potential, BC, NO_2, $PM_{2.5}$, copper (Cu), iron (Fe), zinc (Zn), nickel (Ni), sulphur (S),	BC at birth: range (0.8-3); mean (1.2) $10^{-5}m^{-1}$ NO_2 at birth: range (8.7-59.6); mean (23.1) µg/m^3	Parental reporting of doctor-diagnosed asthma	@ birth, 1, 2, 3, 4, 5, 6, 7, 8, 11-12 and 14 y.o.	Sex, maternal education, parental allergies, breastfeeding, maternal smoking during pregnancy, smoking in the child's home, use of gas for cooking, mould/ dampness in the child's	Using LUR models to model oxidative potential, potential for recall bias in defining the outcome

					vanadium (V)	$PM_{2.5}$ at birth: range (15.3-21.1); mean (16.4) µg/m^3 For oxidative potential; see figure 1 in original paper			home, pets at home, day-care attendance during first year of life and neighbourhood percentage of low income household	
Dell et al. (2014), Canada, Toronto	Case-control	5-9	1,497	LUR modelling, monitoring data weighted by inverse distance to child's residence, distance to highways/ major roadways	NO_2	NO_2 (LUR): range (17.9-47.7); mean (28.3) ppb at birth < 50 m of a major roadway (birth) (13.5% of children)	Parental reporting of doctor-diagnosed asthma	NA	Adjustment variables selected from potential clustering by school, age, sex, parental asthma, prematurity, breastfeeding, low birth weight, crowding, lifetime day-care attendance, income adequacy, respondent's education level and home exposures to tobacco smoke, gas stoves, pets, cockroaches, damp spots and mould. These differ by model	Study participants differed in number of characteristics to non-participants, potential for recall bias in defining the outcome
English et al. (1999), USA, San Diego	Case-control	≤ 14	8,280	Average daily traffic on streets within 168m buffer around residence	NA	Traffic volume at all streets within 550 ft. (cars/day): mean (41,497 controls; 42,880 asthma cases)	Asthma diagnosis based on data from Medi-Cal paid claims database which includes diagnosis based on ICD-9 code 493	NA	Sex, ethnicity, urban status (census block characteristics representing socioeconomic considered but not included in final models)	No adjustment for smoking and heredity, low income population
Hasunuma et al. (2016), Japan, 9 cities and wards	Case-control (nested in SORA)	1.5-3	416	Dispersion modelling including indoor concentration assuming an infiltration rate from outdoor concentration, distance from heavily trafficked roads	EC, NO_x	EC: 6.5% of controls and 5.6% of cases at highest EC level (3.6-7.5 µg/m^3) 18.1% of controls and 17.8% of cases at lowest EC level (1.3-2.4 µg/m^3) NO_x: 6.0% of controls and 4.8% of cases at highest NO_x level (50.9-136.8 ppb) 25.3% of controls and 25.8% of cases at lowest NO_x level (13.9-32.5 ppb)	Asthma defined as a history of two or more attacks of dyspnoea accompanied by wheezing	@ 1.5 and 3 y.o.	Sex, districts, birth season, years of residence, feeding method during the first 3 months of life, familial smoking habits, house structure, heating system, history of pneumonia/bronchitis, empyema and allergic diseases, parental history of asthma, atopic dermatitis and pollinosis, and background air pollution concentrations	Potential for selection bias and follow-up rate low, case-control matching done by geographical region/ area, incidence of asthma identified only between 1.5 and 3 y.o. which is not sufficiently long for effects to reveal themselves, very young age for accurate diagnosis, no adjustment for socioeconomic status, potential for recall bias in defining the outcome

						Distance from traffic: 4.0% of controls and 3.4% of cases at <50 m from a main road 91.7% of controls and 92.3% of cases at ≥ 100 m from a main road				
Nishimura et al. (2013)[c], USA, Chicago, Bronx, Houston, San Francisco, Puerto Rico	2 case-controls (GALA II and SAGE II)	8-21	3,015	Monitoring data at closest four monitors weighted by inverse distance squared to child's residence	NO_2, $PM_{2.5}$, PM_{10}	NO_2 at median birth year: all communities 25[th] and 75[th] percentiles (12.7, 24.0); mean (19.3) ppb $PM_{2.5}$ at median birth year: all communities 25[th] and 75[th] percentiles (8.5, 14.5); mean (11.8) µg/m^3 PM_{10} at median birth year: all communities 25[th] and 75[th] percentiles (23.6, 31.4); mean (27.8) µg/m^3	Reporting of doctor-diagnosed asthma plus ≥ 2 symptoms of coughing, wheezing or shortness of breath in 2 years before recruitment. Cases reporting asthma diagnosis in the first three years of life were excluded. Subgroup analysis undertaken stratified by high/low IgE as a proxy for risk of atopic/non-atopic asthma	NA	Sex, age, geographic region, ethnicity, composite socioeconomic status, familial asthma (in stratified analysis), maternal in utero smoking, environmental tobacco smoke in the household between 0 and 2 years old, and maternal language of preference in sensitivity analysis	Study of Latino Americans and African Americans, case-control matching done by geographical region/ area
Zmirou et al. (2004), France, Paris, Nice, Toulouse, Clermont-Ferrand, Grenoble	Case-control (VESTA)	4-14	390	Traffic density within 300m to road distance ratio	NA	See figure 1 and 2 in original paper	Doctor-diagnosis of asthma by a network of private paediatricians or general practitioners. Cases had not to report doctor-diagnosis of asthma from ≥ 2 years before inclusion	NA	Age, sex, city, smoking during pregnancy, number of months of exposure to maternal smoking at home, day care attendance, parents' social category, number of months of gas usage for cooking, number of months with pets and traces of humidity at home (siblings considered but not included in the final model)	Crude traffic intensity categorization, potential for selection bias, case-control matching done by geographical region/ area, parents of control children had more often a university level education
Deng et al. (2015), China, Changsha	Cross-sectional (CCHH)	3-6	2,490	Monitoring data weighted by inverse distance to child's kindergarten	NO_2, PM_{10} (as a mixture surrogate)	NO_2: range (31-62); mean (48) µg/m^3	Parental reporting of doctor-diagnosed asthma	NA	Sex, age, breastfeeding, living area (downtown, suburban), parental atopy (birth weight, diagnosis of asthma or other allergic diseases) (parental smoking during pregnancy, maternal age,	Excluding low birth weight /premature birth children may bias results towards the null, potential for selection bias by excluding kindergartens with low

						PM_{10}: range (85-138); mean (103) μg/m^3			socioeconomic status (house size and mother occupation) and gestational age were considered but not included in the final models)	response rates and others with missing data, potential for recall bias in defining the outcome, higher likelihood that exposures include other sources of emissions, exposure at kindergarten location is not necessarily the same at home location
Deng et al. (2016), China, Changsha	Cross-sectional (CCHH)	3-6	2.598	Monitoring data weighted by inverse distance to child's kindergarten	NO_2, PM_{10} (as a mixture surrogate)	NO_2: mean (49) μg/m^3 PM_{10}: mean (93) μg/m^3	Parental reporting of doctor-diagnosed asthma	NA	Sex, age, breastfeeding, environmental tobacco smoke at home, furry pets, parental atopy, indoor mould and dampness, indoor renovation	Excluding low birth weight /premature birth children may bias results towards the null, no adjustment for socioeconomic status, potential for selection bias by excluding kindergartens with low response rates and others with missing data, potential for recall bias due to the retrospective questionnaire study, higher likelihood that exposures include industrial emissions, exposure at kindergarten location is not necessarily the same at home location
Kim et al. (2016), Korea, 45 elementary schools	Cross-sectional	6-7	1,828	Monitoring data	CO, NO_2, PM_{10}	CO: 25th and 75th percentiles (570, 740); mean (650) ppb NO_2: 25th and 75th percentiles (22.6, 36.5); mean (29.7) ppb PM_{10}: 25th and 75th percentiles (51.5, 66.8); mean (58.8) μg/m^3	Parental reporting of doctor-diagnosed asthma	NA	Sex, allergic diseases of the parents, education levels of the parents, passive smoking, and family income	Potential for recall bias in defining the outcome, higher likelihood that exposures include other sources of emissions
Liu et al. (2016), China, Shanghai	Cross-sectional (CCHH)	4-6	3,358	Monitoring data	NO_2, PM_{10}	NO_2: birth year - range (36.0, 67.1); mean (55.4) μg/m^3	Parental reporting of doctor-diagnosed asthma	NA	Age, sex, family history of atopy, ownership of the current residence, breastfeeding, home dampness, distance of residence from the nearest main traffic road,	Potential for recall and reporting bias due to the retrospective questionnaire study, higher likelihood that exposures include

	PM_{10}: birth year - range (69.2, 96.6); mean (82.9) µg/m^3		use of heating during winter, renovating the residence or buying new furniture during early lifetime, and household environmental tobacco smoke	other sources of emissions

2.4.2. Asthma Definitions

In line with the systematic review's inclusion criteria, all the included studies, except Gehring et al. (2002) and Morgenstern et al. 2007 and 2008 (Morgenstern et al., 2007, Morgenstern et al., 2008), explicitly included the term '*asthma'* as one outcome for their investigation. In the studies by Gehring et al. (2002), Morgenstern et al. (2007) and Morgenstern et al. (2008), all conducted in Germany, the authors did not examine TRAP associations with the outcome '*asthma'* (doctor-diagnosed asthma) as its prevalence was not sufficiently high in their young populations (< 1%). Instead, they analysed the outcome 'doctor-diagnosed asthmatic/spastic/obstructive bronchitis', reflecting the more cautious diagnosis pattern found in German paediatricians who are reluctant to label a preschool-aged child as asthmatic (Health Effects Institute, 2010, Gehring et al., 2015b). As such, these studies were included.

In the remaining studies, the operational definitions of '*asthma*' varied reflecting the well-known lack of a 'gold standard' for the measurement of the condition (Hansen et al., 2012). Most studies (17 or 41%) exclusively relied on responses to questionnaires using parental-reporting or self-reporting of doctor-diagnosed asthma. 21 studies used a variety of definitions for asthma as shown in Table 1. These notably included more restrictive definitions e.g. combining doctor-diagnosis with symptoms and/or recent asthma medication prescriptions or use, or with symptoms and bronchial hyper reactivity or positive methacholine challenge test. Other definitions included paediatricians' diagnosis, combining recurrent symptoms with response to β-agonist and/or anti-inflammatories (common asthma medications), using disease codes appearing in claim records or doctor billing records from primary care and hospital discharges, and using registry data on dispensed asthma medication.

Five studies classified asthma into its two classical phenotypes: atopic/allergic and non-atopic/non-allergic, using asthma diagnosis combined with blood Immunoglobulin E (IgE) levels to common aero and food allergens (Gehring et al., 2010, Gruzieva et al., 2013, Nishimura et al., 2013, Gehring et al., 2015b, Mölter et al., 2014b). The remaining studies did not attempt to classify the condition.

2.4.3. Exposure Assessment Methods and Pollutants Studied

The exposure to TRAP was assessed using various models, as listed below, but most studies (22 or 54%) used Land-Use Regression (LUR) models. One recent study employed satellite imagery as a new technique for estimating particles exposure (Tétreault et al., 2016). An in-depth review of these models can be found elsewhere

(Health Effects Institute, 2010, Jerrett et al., 2005). The key strengths and weaknesses of each of the encountered methods are summarized in Table 2 and have been described in Khreis and Nieuwenhuijsen (2017). To explore whether the consistency of results across the range of studies was related to the methodological quality of the exposure assessment (Jerrett, 2007), the TRAP exposure assessment methods were categorized into 5 categories listed below. This was to group available risk estimates under similar exposure models to give an indication whether part of the differences in findings may be attributable to differences in exposure assessments. The grouped risk estimates can be found in the supplementary data of Khreis et al. (2017d). The exposure assessment categories were:

1. TRAP surrogates (e.g. proximity to roadways) → 16 studies;
2. traffic-related air pollutant concentrations measured at fixed-site monitoring stations → 11 studies;
3. traffic-related air pollutant concentrations estimated by LUR modelling → 22 studies;
4. traffic-related air pollutant concentrations estimated by dispersion modelling → 7 studies;
5. traffic-related air pollutant concentrations measured at the individual residential address level → 1 study;
6. traffic-related air pollutant concentrations measured by Satellite Imagery → 1 study.

In studies using measured or modelled pollutant concentrations to represent TRAP exposures in the main analyses: NO_2 was the pollutant most studied (31 studies), followed by $PM_{2.5}$ (18 studies), BC/$PM_{2.5}$ absorbance (15 studies) and PM_{10} (14 studies). Less frequently studied pollutants were NO_x (6 studies), EC (4 studies), CO (3 studies), PM_{coarse} (3 studies), NO (2 studies) and several particulate matter composition elements including copper (Cu), iron (Fe), zinc (Zn), nickel (Ni), sulphur (S) and vanadium (V); each of which were investigated in two studies (Gehring et al., 2015a, Kerkhof et al., 2010). No study was found to examine ultra-fine particles, yet one study investigated associations with Oxidative Potential (OP), a measure of the inherent capacity of fine particulate matter to oxidize target molecules (Yang et al., 2016). In studies employing LUR modelling to estimate TRAP, there was evidence that the models' validity differed across pollutants. LUR models captured variability in mean BC and NO_2 concentrations best and were less adequate in estimating mean $PM_{2.5}$ concentrations (see supplementary data of Khreis et al. (2017d)).

TRAP exposures were almost exclusively assigned based on the participants' residential addresses, with a few exceptions where routine measurements from fixed-site monitoring stations near schools (Shima and Adachi, 2000, Shima et al., 2002) and children's nurseries (Deng et al., 2015, Deng et al., 2016) were used to represent exposures. Only 8 studies, 5 of which published after 2014, considered children's mobility at older ages and assigned time-weighted TRAP exposures at day-care-centres and schools (Gruzieva et al., 2013, McConnell et al., 2010, Zmirou et al., 2004, Hasunuma et al., 2016, Mölter et al., 2014a, Yamazaki et al., 2014) and other locations where the child spent significant time (Brunst et al., 2015, LeMasters et al., 2015), alongside residence.

2.4.4. Quality Assessment

Results from the CASP assessment are shown in the supplementary data of Khreis et al. (2017d). Overall, the included studies were considered of a good quality to make an appropriate evaluation of the relationship between TRAP and asthma development, as mainly reported by questionnaires. Some of the limitations identified related to non-representative samples, evaluating asthma by questionnaires only and not adjusting for important confounders. Specific issues arising from the assessment of the individual studies are also summarized in the last column Table 1. More general issues identified across the overall body of evidence are presented next.

Cohort studies were generally considered to be superior to case-control studies and cross-sectional studies as they comprise more extensive follow-up and a lower likelihood for certain biases such as selection bias. As all studies met the inclusion criteria of this systematic review and examined the relationship between TRAP exposures and subsequent development of asthma in children from birth to 18 years of age, all studies were considered to address a clearly focused issue. In cohort and cross-sectional studies, only three studies were considered to have recruited their cohorts in an acceptable manner. Recruiting a representative sample is very hard in birth cohorts because of the long-term commitment needed and most, if not all, birth cohorts fail to recruit an entirely representative sample of the whole population because of low recruitment rates and lower inclusion of certain groups like lower socioeconomic status groups and ethnic minorities. It was difficult to make judgment about eight studies which reported no information about the general population and response rates.

Table 2 Pros and Cons of Exposure Models used in the Systematic Review Literature, Source: (Own Work)

Exposure model	Resolution		Specificity to traffic	Pros	Cons
	Spatial	Temporal			
TRAP surrogates e.g. proximity to ‘major roads’ or ‘freeways’	-	- -	+	Intuitive, simple and cost effective, can provide insight on which pollutants are more likely to be responsible if proximity assessed for smaller length sections, more insightful when complemented with vehicles counts and composition, low need for updated data	Assumes a road of a certain type or size corresponds to a certain amount of traffic, sometime uses self-reported traffic intensity (collected via questionnaires) which can be subjective, assumes all pollutants disperse similarly and provides no information on levels of pollutants, cannot consider street canyon effects, generally does not consider compounded effects of proximity to multiple roads, disregards exposure variability due to mobility/individual activity
Air pollutants measurements from fixed-site monitoring stations	- -	+ +	--	High and continuous temporal resolution, actual measurements rather than estimates, cost effective, can provide large sample sizes, medium need for updated data	Not present at all locations, locations usually based on regulatory (not scientific) purposes, cannot consider street canyon effects (unless located in a street canyon), conceals persons’ differences because of a mismatch between data used to estimate exposure and actual subjects’ locations, potential for significant amounts of missing data in practice, quality of the data depends on quality of data ratification and verification, disregards exposure variability due to mobility/individual activity
Air pollutant measurements from residential (stationary) samplers	+ +	-	-	Provides individualized data, captures spatial variability in exposure between study subjects, actual measurements rather than estimates, cost effective for select pollutants (e.g. NO_2), medium need for updated data	Only practical/ feasible in small timeframes and populations, logistic and costs concerns, not available or cost prohibitive (e.g. ultra-fine particles) for all pollutants of concern, disregards exposure variability due to mobility/individual activity
Remote sensing	+	-	--	Can provide estimates for large areas and in areas where measurements or models are not available (e.g. low- and medium-income countries), relatively standardized method across regions, medium need for updated data	Availability depends on satellite presence (i.e. time resolution is limited), crude spatial resolution (10 *10 km), only available for select pollutants, challenging to assess errors in estimates, cannot consider street canyon effects, disregards exposure variability due to mobility/individual activity
Land-use regression models	+	- -	+	Assume independence between sampled locations, good agreement between measured and estimated averages of NO_2, less with PM, modelling based on measurements and information around measurement points, relatively easy to collate input data, practical, low costs, medium need for updated data	Only reflect the predictors used in the model, subject to varying uncertainties amongst different pollutants, the true contribution of traffic to the regression is not always known or reported, difficult to take into account street canyon effects; meteorology and atmospheric chemistry, cannot assess episodic short-term exposures, the quality of the data representing ‘meaningful’ predictors may be an issue and will affect the overall accuracy of the model, the model’s outputs are sensitive to the locations and density of the sampling sites, generally disregards exposure variability due to mobility/individual activity
Atmospheric dispersion models	+ +	+ +	++	Continuous exposure metric, traffic-specific i.e. based on traffic flows, traffic emissions, meteorology and atmospheric chemistry, covers relatively large areas, can assess episodic short-term & long-term exposures, can consider street canyon effects through optional built-in street canyon model in many packages, considers compounded effects of proximity to multiple roads, medium need for updated data	Severe data demands, resource intensive, at the mercy of the emission factors inputted in the model (subject to high uncertainty), meteorology at the exposure scale is influenced by complex physical features including traffic turbulence which is difficult to consider, overestimates pollution levels during periods of calm wind, generally disregards exposure variability due to mobility/individual activity

The potential for selection bias was highlighted in 25 cohort studies. Reasons for selection bias included special cohort characteristics (e.g. high-risk populations); very small sample size; high non-response and exclusion rates and important differences between participants and nonparticipants, mainly reflected in differing socioeconomic status. This may not always affect the internal validity of the observations, but it may affect the external validity. Most cohort studies reported good rates of retention at follow-up and only eight studies reported losing > 30% of the initial eligible cohort. Only 6 studies following children below the age of 6 years were considered to not be sufficiently long for investigating asthma as it is difficult to assess asthma in children below school age.

In case-control studies, potential for selection bias was highlighted in two studies. Reasons for selection bias included high non-response or exclusion rates. No study has undertaken power calculations to determine the sufficient sample size. Three of the case-control studies (Hasunuma et al., 2016, Zmirou et al., 2004, Nishimura et al., 2013) matched cases to controls by geographical area, which may introduce bias by reducing exposure contrast between cases and controls (Vrijheid et al., 2011).

Overall, most studies (28 or 68%) have identified and adequately adjusted for important confounders; with heredity, smoking and/or second-hand smoke exposure and socioeconomic status being the most reported and the ones considered the most important. Ten cohort and cross-sectional studies did not adjust for heredity; smoking and/or second-hand smoke exposure or socioeconomic status and 3 case-control studies did not adjust for one or more of these variables. Six studies excluded low birth weight/premature birth children from the analysis (Clark et al., 2010, Deng et al., 2015, Gehring et al., 2002, Wang et al., 2016c, Deng et al., 2016, Fuertes et al., 2013). These exclusion may bias results toward the null because low birth weight and gestational period may also act on the causal pathway between air pollution and asthma (Clark et al., 2010) and the exclusion of these groups may exclude a more sensitive population. Studies using parental reporting of doctor-diagnosed asthma (21) were subject to recall bias in defining the outcome, but the lack of a better asthma metric to be used in large epidemiological studies limits alternatives. All studies adequately measured the exposure by always using objective, rather than subjective, measurements and classifying subjects into exposure groups using the same procedure. However, there are limitations of each exposure metric used as overviewed in Section 2.4.3. and most studies do not incorporate mobility patterns in older children which limits capturing the true exposure levels and likely leads to exposure misclassification (Nieuwenhuijsen, 2015). Some of the limitations described above were dealt with in sensitivity analyses leaving out certain studies (Section 2.4.5.), but this did not result in materially different risk estimates than reported in the main analyses which included all eligible studies.

2.4.5. Meta-Analytic Summary Risks Estimates

Results from the random-effects meta-analysis are shown in Figure 5 to Figure 9. Results from the fixed-effects meta-analysis are shown in the supplementary data of Khreis et al. (2017d). Both random- and fixed-effects meta-analyses results are numerically presented in Table 3, alongside the heterogeneity estimates and the number of studies included in each analysis. Results from the sensitivity analyses are also given in Table 3. The funnel plots are shown in the supplementary data of Khreis et al. (2017d). The results for each pollutant are described in turn, next.

- **<u>Risks in Association with BC Exposures</u>**

In the overall meta-analysis for BC, the random-effects overall risk estimate for asthma development was statistically significantly increased (for 0.5 x 10^{-5} m^{-1} BC, overall risk estimate = 1.08, 95% CI 1.03, 1.14), with 0% estimated heterogeneity (Figure 5). Results from the fixed-effects model were comparable (Table 3). The overall risk estimate remained increased and statistically significant, with no estimated heterogeneity, in all sensitivity analyses. In the age-specific meta-analysis, the random-effects overall risk estimate was also statistically significantly increased for both age groups, but heterogeneity increased in the ≤ 6 years' old. The overall risk estimate was generally robust in sensitivity analyses, although one cohort (the Dutch PIAMA cohort) was driving the positive associations in the older age group (Table 3).

Study or Subgroup	log[Odds Ratio]	SE	Weight	Odds Ratio IV, Random, 95% CI
Carlsten et al. 2010 - at 7 y.o.	0.0397	0.1061	6.3%	1.04 [0.85, 1.28]
Clark et al. 2010 LUR - at mean age of 4 y.o.	0.0655	0.0312	73.1%	1.07 [1.00, 1.14]
Gehring et al. 2015 b - BAMSE birth to 16 y.o.	-0.0105	0.1707	2.4%	0.99 [0.71, 1.38]
Gehring et al. 2015 b - PIAMA birth to 14 y.o.	0.1662	0.0804	11.0%	1.18 [1.01, 1.38]
Gehring et al. 2015b - GINI&LISA South birth to 15	0.124	0.1831	2.1%	1.13 [0.79, 1.62]
Gehring et al. 2105b - GINI&LISA North birth to 15	0.0322	0.2613	1.0%	1.03 [0.62, 1.72]
Krämer et al. 2009 - 4 to 6 y.o.	0.14842	0.14567461	3.4%	1.16 [0.87, 1.54]
Mölter et al. 2014 b - MAAS only birth to 8 y.o.	0.4293	0.344	0.6%	1.54 [0.78, 3.01]
Total (95% CI)			**100.0%**	**1.08 [1.03, 1.14]**

Heterogeneity: $Tau^2 = 0.00$; $Chi^2 = 3.13$, df = 7 (P = 0.87); $I^2 = 0\%$
Test for overall effect: Z = 2.96 (P = 0.003)

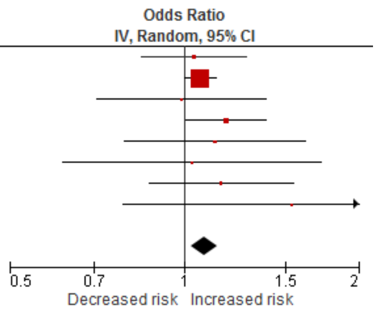


Figure 5 BC Random-Effects Meta-Analysis. Individual and Summary Random-Effects Estimates for Associations between BC per 0.5 x 10^{-5} m^{-1} and Asthma at Any Age, Source: Own Work (RevMan 5)

- **<u>Risks in Associations with NO_2 Exposures</u>**

In the overall meta-analysis for NO_2, the random-effects overall risk estimate for asthma development was statistically significantly increased (for 4 µg/m^3 NO_2, overall risk estimate = 1.05, 95% CI 1.02, 1.07). Yet, there was substantial and statistically significant heterogeneity (Figure 6). Results from the fixed-effects model were comparable (Table 3). Random-effects overall risk estimate remained statistically significantly increased in all sensitivity analyses. In the age-specific meta-analysis, the random-effects overall risk estimate was increased and statistically significant for both age groups. Heterogeneity remained high in both analyses (Table 3).

Study or Subgroup	log[Odds Ratio]	SE	Weight	Odds Ratio IV, Random, 95% CI
Carlsten et al. 2010 - at 7 y.o.	0.2253	0.1448	0.6%	1.25 [0.94, 1.66]
Clark et al. 2010 LUR - at mean age of 4 y.o.	0.0489	0.0171	9.5%	1.05 [1.02, 1.09]
Dell et al. 2014 LUR - 5 to 9 y.o.	0.039	0.04	5.0%	1.04 [0.96, 1.12]
Deng et al. 2016 - 3 to 6 y.o.	0.1374	0.0689	2.4%	1.15 [1.00, 1.31]
Gehring et al. 2015 b - BAMSE birth to 16 y.o.	0.0397	0.0498	3.8%	1.04 [0.94, 1.15]
Gehring et al. 2015 b - PIAMA birth to 14 y.o.	0.0665	0.0246	7.8%	1.07 [1.02, 1.12]
Gehring et al. 2015b - GINI&LISA North birth to 15	-0.0679	0.1235	0.8%	0.93 [0.73, 1.19]
Gehring et al. 2015b - GINI&LISA South birth to 15	-0.0252	0.0602	2.9%	0.98 [0.87, 1.10]
Jerret et al. 2008 - 10 to 18 y.o.	0.0874	0.033	6.1%	1.09 [1.02, 1.16]
Kim et al. 2016 - 6 to 7 y.o.	-0.0214	0.0219	8.4%	0.98 [0.94, 1.02]
Krämer et al. 2009 - 4 to 6 y.o.	0.0698	0.069	2.3%	1.07 [0.94, 1.23]
Liu et al. 2016 - 4 to 6 years old	0.0877	0.0215	8.5%	1.09 [1.05, 1.14]
MacIntyre et al. 2014 - CAPPS&SAGE only birth to 8	0.1111	0.1268	0.8%	1.12 [0.87, 1.43]
McConnell et al. 2010 - 4th to 6th grade	0.0698	0.0281	7.1%	1.07 [1.01, 1.13]
Mölter et al. 2014 b - MAAS only birth to 8 y.o.	0.574	0.2374	0.2%	1.78 [1.11, 2.83]
Nishimura et al. 2013 - 8 to 21 y.o.	0.0632	0.0269	7.3%	1.07 [1.01, 1.12]
Oftedal et al. 2009 - birth to 10 y.o.	-0.0359	0.0196	8.9%	0.96 [0.93, 1.00]
Ranzi et al. 2014 - birth to 7 y.o.	0.0289	0.0701	2.3%	1.03 [0.90, 1.18]
Shima et al. 2002 - 6 to 12 y.o.	0.1136	0.0534	3.5%	1.12 [1.01, 1.24]
Tétreault et al. 2016 - birth to 12 y.o.	0.0153	0.0048	11.6%	1.02 [1.01, 1.03]
Total (95% CI)			**100.0%**	**1.05 [1.02, 1.07]**

Heterogeneity: Tau² = 0.00; Chi² = 54.38, df = 19 (P < 0.0001); I² = 65%
Test for overall effect: Z = 3.76 (P = 0.0002)

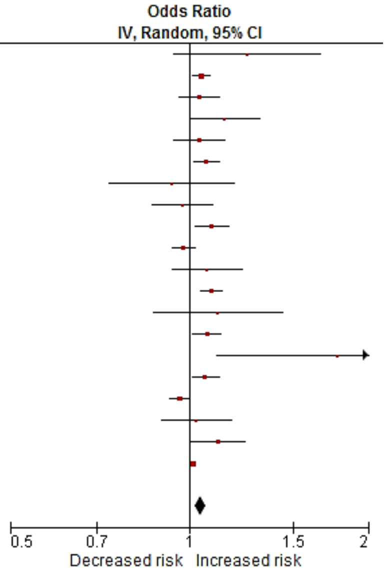


Figure 6 NO_2 Random-Effects Meta-Analyses. Individual and Summary Random-Effects Estimates for Associations between NO_2 per 4 µg/m^3 and Asthma at Any Age, Source: Own Work (RevMan 5)

- **<u>Risks in Association with NO_x Exposures</u>**

In the overall meta-analysis for NO_x, the random-effects overall risk estimate for asthma development was increased but was not statistically significant (for 30 µg/m^3 NO_x, overall risk estimate = 1.48, 95% CI 0.89, 2.45). There was substantial and statistically significant heterogeneity which was the highest detected across all analyses (Figure 7).

Results from the fixed-effects model, however, showed a statistically significantly increased risk, with substantial and statistically significant heterogeneity (Table 3). In the age-specific meta-analyses, the random-effects overall risk estimates were increased in children diagnosed > 6 years old only, but similarly to the overall analysis, these risk estimates were statistically insignificant (Table 3).

Study or Subgroup	log[Odds Ratio]	SE	Weight	Odds Ratio IV, Random, 95% CI
McConnell et al. 2010 - 1st to 4th grade	0.4457	0.1753	16.5%	1.56 [1.11, 2.20]
Mölter et al. 2014 b - BAMSE at 8 y.o.	-0.1415	0.2444	15.4%	0.87 [0.54, 1.40]
Mölter et al. 2014 b - GINI/LISA North at 8 y.o.	0.143	0.3189	14.0%	1.15 [0.62, 2.16]
Mölter et al. 2014 b - GINI/LISA South at 8 y.o.	-0.4117	0.3601	13.2%	0.66 [0.33, 1.34]
Mölter et al. 2014 b - MAAS at 8 y.o.	0.9065	0.6848	7.9%	2.48 [0.65, 9.48]
Mölter et al. 2014 b - PIAMA at 8 y.o.	0.3467	0.1726	16.5%	1.41 [1.01, 1.98]
Yamazaki et al. 2014 - at 6 to 9 y.o.	1.497	0.183	16.4%	4.47 [3.12, 6.40]
Total (95% CI)			**100.0%**	**1.48 [0.89, 2.45]**

Heterogeneity: Tau² = 0.37; Chi² = 45.43, df = 6 (P < 0.00001); I² = 87%
Test for overall effect: Z = 1.52 (P = 0.13)

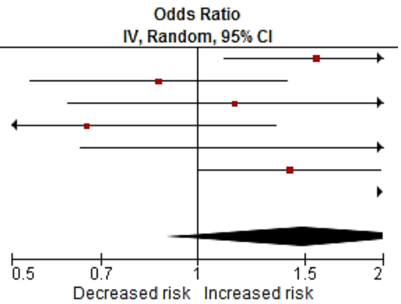


Figure 7 NO_x Random-Effects Meta-Analyses. Individual and Summary Random-Effects Estimates for Associations between NO_x per 30 μg/m³ and Asthma at Any Age, Source: Own Work (RevMan 5)

- **Risk in Association with $PM_{2.5}$ Exposures**

In the overall meta-analysis for $PM_{2.5}$, the random-effects overall risk estimate for asthma development was statistically significantly increased (for 1 μg/m³ $PM_{2.5}$, overall risk estimate = 1.03, 95% CI 1.01, 1.05), with little heterogeneity (Figure 8). Results from all sensitivity analysis showed a statistically significantly increased risk of asthma with $PM_{2.5}$ exposures, as did the fixed-effects model (Table 3). Of note was the significant reduction in heterogeneity in sensitivity analysis excluding the high risk birth cohort (Carlsten et al., 2010). In the age-specific meta-analyses of children ≤ 6 years old age, the results were positive but not statistically significant, whilst results from older children supported a statistically significantly increased risk, with reduced heterogeneity (Table 3).

Study or Subgroup	log[Odds Ratio]	SE	Weight	Odds Ratio IV, Random, 95% CI
Carlsten et al. 2010 - at 7 y.o.	0.276	0.1082	0.9%	1.32 [1.07, 1.63]
Clark et al. 2010 LUR - at mean age of 4 y.o.	0.01	0.0101	32.7%	1.01 [0.99, 1.03]
Gehring et al. 2015 b - BAMSE birth to 16 y.o.	0.0259	0.0385	6.2%	1.03 [0.95, 1.11]
Gehring et al. 2015 b - PIAMA birth to 14 y.o.	0.1093	0.0546	3.3%	1.12 [1.00, 1.24]
Gehring et al. 2015b - GINI&LISA North birth to 15	0.066	0.1352	0.6%	1.07 [0.82, 1.39]
Gehring et al. 2015b - GINI&LISA South birth to 15	-0.0266	0.0861	1.4%	0.97 [0.82, 1.15]
McConnell et al. 2010 - 1st to 4th grade	0.0291	0.0177	19.8%	1.03 [0.99, 1.07]
Mölter et al. 2014 b - MAAS only birth to 8 y.o.	-0.1688	0.8068	0.0%	0.84 [0.17, 4.11]
Nishimura et al. 2013 - 8 to 21 y.o.	0.0296	0.0691	2.1%	1.03 [0.90, 1.18]
Tétreault et al. 2016 - birth to 12 y.o.	0.0396	0.0099	33.1%	1.04 [1.02, 1.06]
Total (95% CI)			**100.0%**	**1.03 [1.01, 1.05]**

Heterogeneity: Tau² = 0.00; Chi² = 12.56, df = 9 (P = 0.18); I² = 28%
Test for overall effect: Z = 2.96 (P = 0.003)

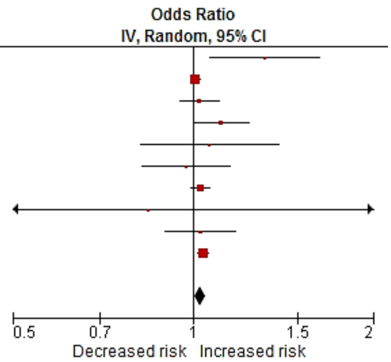


Figure 8 $PM_{2.5}$ Random-Effects Meta-Analyses. Individual and Summary Random-Effects Estimates for Associations between $PM_{2.5}$ per 1 μg/m³ and Asthma at Any Age, Source: Own Work (RevMan 5)

- **Risks in Association with PM_{10} Exposures**

In the overall meta-analysis for PM_{10}, the random-effects overall risk estimates for asthma development was statistically significantly increased (for 2 μg/m³ PM_{10}, overall risk estimate = 1.05, 95% CI 1.02, 1.08), with little heterogeneity (Figure 9).

Results from the fixed-effects model were comparable (Table 3) and sensitivity analyses supported these findings. The age specific analysis showed increased risks in both age groups. Sensitivity analysis supported these findings in the younger age group only, whereas the associations disappeared in the older age group (Table 3).

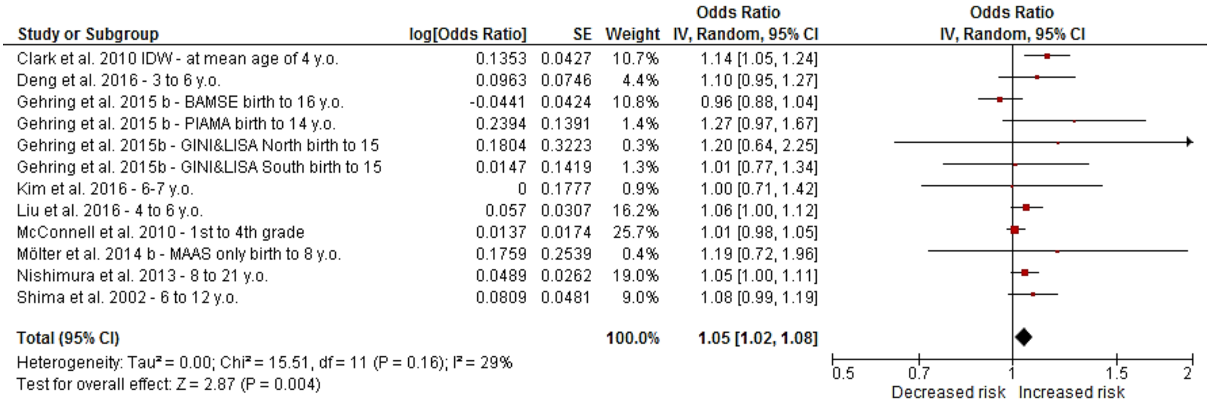


Figure 9 PM_{10} Random-Effects Meta-Analyses. Individual and Summary Random-Effects Estimates for Associations between PM_{10} per 2 μg/m^3 and Asthma at Any Age, Source: Own Work (RevMan 5)

2.4.6. Publication Bias

The funnel plots are shown in the supplementary data of Khreis et al. (2017d). In general, there were not enough studies to comprehensively examine publication bias. However, it seemed that there is little indication for publication bias except for the NO_x analysis where the funnel plot was clearly asymmetrical.

Table 3 Overall and Age-Specific Meta-Analyses Results

	Exposure	Overall random-effects meta-analysis OR (95% CI)	Overall fixed-effects meta-analysis OR (95% CI)	Number of included studies	Sensitivity analysis 1: excluding study/ studies contributing to largest weight in random-effects meta-analysis OR (95% CI)	Sensitivity analysis 2: excluding case-control studies in random-effects meta-analysis OR (95% CI)	Sensitivity analysis 3: excluding cross-sectional studies in random-effects meta-analysis OR (95% CI)	Sensitivity analysis 4: excluding studies with special characteristics in random-effects meta-analysis OR (95% CI)
Overall meta-analysis	BC	**1.08 (1.03, 1.14)**, I^2 = 0%, P = 0.87	**1.08 (1.03, 1.14)**, I^2 = 0%, P = 0.87	8	Study: Clark et al. 2010 (Weight = 73.1%) **1.12 (1.01, 1.24)**, I^2 = 0%, P = 0.88	Study: Clark et al. 2010 **1.12 (1.01, 1.24)**, I^2 = 0%, P = 0.88	None included	Study: Carlsten et al. 2010 (reason: high risk birth cohort) **1.09 (1.03, 1.15)**, I^2 = 0%, P = 0.81
	NO_2	**1.05 (1.02, 1.07)**, I^2 = 65%, P = 0.0001	**1.02 (1.01, 1.03)**, I^2 = 65%, P = 0.0001	20	Study: Tétreault et al. 2016 (Weight = 11.6%) **1.05 (1.02, 1.08)**, I^2 = 61%, P = 0.0003	Studies: Clark et al. 2010, Dell et al. 2014, Nishimura et al. 2013 **1.04 (1.02, 1.07)**, I^2 = 67%, P = 0.0001	Studies: Deng et al. 2015, Kim et al. 2016, Liu et al. 2016 **1.04 (1.02, 1.07),** I^2 = 58%, P = 0.001	Study: Carlsten et al. 2010 (reason: high risk birth cohort) **1.04 (1.02, 1.07)**, I^2 = 66%, P = 0.0001
	NO_x	1.48 (0.89, 2.45), I^2 = 87%, P = 0.00001	**1.68 (1.42, 1.99)**, I^2 = 87%, P = 0.00001	7	Study: Mölter et al. 2014 b – PIAMA component (Weight = 16.5%) 1.49 (0.79, 2.82), I^2 = 89%, P = 0.00001	None included	None included	None included
	$PM_{2.5}$	**1.03 (1.01, 1.05)**, I^2 = 28%, P = 0.18	**1.03 (1.02, 1.04),** I^2 = 28%, P = 0.81	10	Study: Tétreault et al. 2016 (Weight = 33.1%) **1.03 (1.00, 1.05)**, I^2 = 20%, P = 0.26	Studies: Clark et al. 2010, Nishimura et al. 2013 **1.04 (1.02, 1.06)**, I^2 = 8%, P = 0.37	None included	Study: Carlsten et al. 2010 (reason: high risk birth cohort) **1.03 (1.01, 1.04)**, I^2 = 0%, P = 0.51
	PM_{10}	**1.05 (1.02, 1.08)**, I^2 = 29%, P = 0.16	**1.04 (1.02, 1.06),** I^2 = 29%, P = 0.16	12	Study: McConnell et al. 2010 (Weight = 25.7%) **1.06 (1.02, 1.10)**, I^2 = 16%, P = 0.29	Studies: Clark et al. 2010, Nishimura et al. 2013 **1.03 (1.00, 1.06)**, I^2 = 4%, P = 0.40	Study: Deng et al. 2015, Kim et al. 2016, Liu et al. 2016 **1.05 (1.00, 1.10)**, I^2 = 44%, P = 0.07	None included
Age-specific meta-analysis ≤ 6 years' old	**Exposure**	**Age-specific ≤ 6 years old random-effects meta-analysis OR (95% CI)**	**Age-specific ≤ 6 years old fixed-effects meta-analysis OR (95% CI)**	**Number of included studies**	**Sensitivity analysis 1: excluding study/ studies contributing to largest weight in random-effects meta-analysis OR (95% CI)**	**Sensitivity analysis 2: excluding case-control studies in random-effects meta-analysis OR (95% CI)**	**Sensitivity analysis 3: excluding cross-sectional studies in random-effects meta-analysis OR (95% CI)**	**Sensitivity analysis 3: excluding studies with special characteristics in random-effects meta-analysis OR (95% CI)**
	BC	**1.17 (1.01, 1.36)**, I^2 = 45%, P = 0.12	**1.09 (1.03, 1.16)**, I^2 = 45%, P = 0.12	5	Study: Clark et al. 2010 (Weight = 47.4%) **1.27 (1.05, 1.54)**, I^2 = 42%, P = 0.18	Study: Clark et al. 2010 **1.27 (1.05, 1.54)**, I^2 = 02%, P = 0.29	None included	None included
	NO_2	**1.08 (1.04, 1.12)**, I^2 = 26%, P = 0.23	**1.07 (1.05, 1.10)**, I^2 = 26%, P = 0.23	7	Study: Clark et al. 2010 (Weight = 38.6%) **1.10 (1.06, 1.13)**, I^2 = 0%, P = 0.42	Study: Clark et al. 2010 **1.10 (1.06, 1.213)**, I^2 = 0%, P = 0.42	Study: Deng et al. 2015, Liu et al. 2016 **1.07 (1.02, 1.36)**, I^2 = 32%, P = 0.21	None included

	NO_x	1.02 (0.69, 1.49), I^2 = 69%, P = 0.007	1.02 (0.85, 1.24), I^2 = 69%, P = 0.007	6	Study: Mölter et al. 2014 b – PIAMA component (Weight = 22.9%) 0.97 (0.59, 1.58), I^2 = 70%, P = 0.010	Study: Hasunuma et al. 2016 1.15 (0.80, 1.66), I^2 = 52%, P = 0.08	None included	None included
	$PM_{2.5}$	1.04 (0.99, 1.11), I^2 = 41%, P = 0.16	**1.02 (1.00, 1.04)**, I^2 = 41%, P = 0.16	4	Study: Clark et al. 2010 (Weight = 58.8%) **1.09 (1.02, 1.17)**, I^2 = 0%, P = 0.94	Study: Clark et al. 2010 (Weight = 58.8%) **1.09 (1.02, 1.17)**, I^2 = 0%, P = 0.94	None included	None included
	PM_{10}	**1.09 (1.04, 1.15)**, I^2 = 12%, P = 0.34	**1.09 (1.04, 1.14)**, **I^2 = 12%**, **P = 0.34**	5	Study: Liu et al. 2016 (Weight = 49.2%) **1.09 (1.02, 1.17)**, I^2 = 34%, P = 0.21	Study: Clark et al. 2010 **1.07 (1.01, 1.12)**, I^2 = 0%, P = 0.46	Study: Deng et al. 2015, Liu et al. 2016 **1.12 (1.00, 1.25)**, I^2 = 24%, P = 0.27	None included

Age-specific meta-analysis > 6 years' old	Exposure	Age-specific > 6 years old random-effects meta-analysis OR (95% CI)	Age-specific > 6 years old fixed-effects meta-analysis OR (95% CI)	Number of included studies	Sensitivity analysis 1: excluding study/ studies contributing to largest weight in random-effects meta-analysis OR (95% CI)	Sensitivity analysis 2: excluding case-control studies in random-effects meta-analysis OR (95% CI)	Sensitivity analysis 3: excluding cross-sectional studies in random-effects meta-analysis OR (95% CI)	Sensitivity analysis 3: excluding studies with special characteristics in random-effects meta-analysis OR (95% CI)
	BC	**1.12 (1.00, 1.24)**, I^2 = 0%, P = 0.79	**1.12 (1.00, 1.24),** I^2 = 0%, P = 0.79	6	Study: Gehring et al. 2015 b – PIAMA component (Weight = 46.8%) 1.06 (0.92, 1.23), I^2 = 0%, P = 0.83	None included	None included	Carlsten et al. 2010 (reason: high risk birth cohort) **1.15 (1.01, 1.30)**, I^2 = 0%, P = 0.78
	NO_2	**1.03 (1.00, 1.06)**, I^2 = 62%, P = 0.001	**1.02 (1.01, 1.03)**, I^2 = 62%, P = 0.001	14	Study: Tétreault et al. 2016 (Weight = 17.6%) **1.04 (1.00, 1.08)**, **I^2 = 65%**, **P = 0.02**	Study: Nishimura et al. 2013 **1.03 (1.00, 1.06)**, I^2 = 62%, P = 0.002	Study: Kim et al. 2016 **1.04 (1.01, 1.07)**, **I^2 = 62%**, **P = 0.002**	Carlsten et al. 2010 (reason: high risk birth cohort) **1.03 (1.00, 1.06)**, I^2 = 63%, P = 0.001
	NO_x	1.46 (0.77, 2.78), I^2 = 89%, P = 0.00001	**1.72 (1.41, 2.09), I^2 = 89%**, **P = 0.00001**	6	Study: Mölter et al. 2014 b – PIAMA component (Weight = 19.1%) 1.47 (0.62, 3.52), I^2 = 91%, P = 0.00001	None included	None included	None included
	$PM_{2.5}$	**1.04 (1.02, 1.07)**, I^2 = 3%, P = 0.41	**1.04 (1.02, 1.06),** I^2 = 13%, P = 0.41	8	Study: Tétreault et al. 2016 (Weight = 80.3%) **1.06 (1.00, 1.12)**, I^2 = 12%, P = 0.34	Study: Nishimura et al. 2013 **1.05 (1.01, 1.09)**, I^2 = 16%, P = 0.31	None included	Carlsten et al. 2010 (reason: high risk birth cohort) **1.04 (1.02, 1.06)**, I^2 = 0%, P = 0.78
	PM_{10}	**1.04 (1.00, 1.08)**, I^2 = 5%, P = 0.39	**1.04 (1.00, 1.08),** I^2 = 5%, P = 0.39	8	Study: Nishimura et al. 2013 (Weight = 51.0%) 1.03 (0.96, 1.11), I^2 = 14%, P = 0.32	Study: Nishimura et al. 2013 1.03 (0.96, 1.11), I^2 = 14%, P = 0.32	Study: Kim et al. 2016 1.04 (0.99, 1.09), I^2 = 18%, P = 0.29	None included

2.4.7. Sexes and Atopic and Non-Atopic Asthma Differences

There was some suggestion that effects may be different by sex, although this was inconsistent. Seven out of 11 studies which examined whether there was a differential susceptibility or modification in the effects of TRAP by sex reported such differences. The individual study findings from those 7 papers are overviewed next.

Clark et al. (2010) showed that the risk estimates for all traffic-related pollutants were consistently higher for girls than for boys. This was most prominent for BC exposures (for 0.5 x 10^{-5} m^{-1} BC, adjusted OR = 1.28 (95% CI, 1.05, 1.56) for girls versus 1.07 (95% CI, 0.92, 1.24) for boys). Nishimura et al. (2013) showed that when compared to boys, girls seemed to be less susceptible to NO_2, but more susceptible to $PM_{2.5}$ and PM_{10}; although these differences were not statistically significant (differences can be found in the paper's associated supplementary material). Oftedal et al. (2009) showed that NO_2 exposures were associated with a higher but statistically non-significant risk of asthma in girls only (IQR increase of NO_2 exposure before asthma onset was associated with adjusted RR = 0.73 (95% CI, 0.56, 0.95) in boys versus 1.05 (95% CI, 0.74, 1.49) in girls). Shima et al. (2003) showed that the association between incidence of asthma and living at 0-49 m from trunk roads is slightly higher in girls, although non-significant (adjusted OR = 3.77 (95% CI, 1.00, 14.16) in boys and 4.03 (95% CI, 0.90, 17.96) in girls). The three remaining studies (Carlsten et al., 2010, Deng et al., 2015, Gehring et al., 2015b) indicated an increased risk of TRAP-associated asthma in boys. Two of these latter studies argued that in infancy, the airway size is smaller in boys than in girls, on average (for 10 µg/m^3 first year NO_2 adjusted OR = 1.57 (95% CI 1.08, 2.26) in boys and 1.51 (95% CI 0.87, 2.61) in girls) (Deng et al., 2015), and that the sex differences detected were neither statistically significant nor clinically relevant (differences only shown graphically in the paper's associated supplementary material) (Gehring et al., 2015b). The third which was the study by Carlsten et al. (2010) was a high risk cohort where boys are expected to have had more respiratory symptoms to start with, something which might have obscured air pollution effects (Clougherty, 2010).

In the 5 studies which phenotyped asthma as atopic/allergic and non-atopic/non-allergic, ORs were only increased (Gehring et al., 2010, Gehring et al., 2015b, Mölter et al., 2014b), or were higher in magnitude (Gruzieva et al., 2013, Nishimura et al., 2013) for the non-atopic/non-allergic asthma phenotype. The detailed data on the associations between TRAP and atopic versus non-atopic asthma can be found in the supplementary data of Khreis et al. (2017d).

2.5. Discussion

2.5.1. Summary

In this systematic review and meta-analysis, 41 studies, published between 1999 and September 2016 and investigating the association between the exposure to TRAP and the subsequent development of childhood asthma, were synthesized. The selected studies were assessed for their quality and were considered of a good quality to make an appropriate evaluation of the relationship between TRAP and asthma development; as mainly reported by questionnaires. The main limitations identified in the literature related to non-representative samples, evaluating asthma by questionnaires only and in some instances not adjusting for important confounders such as heredity and smoke exposure.

This systematic review and meta-analysis provided evidence for a positive association between TRAP exposures and subsequent childhood asthma development. These results are concordant with most previous individual studies (see supplementary data in Khreis et al. (2017d)). There is also considerable support from other syntheses for the hypothesis that childhood exposure to TRAP contributes to their development of asthma (Bowatte et al., 2015, Anderson et al., 2013, Health Effects Institute, 2010). Discordant findings were reported by a small number of studies, but some of these were particularly highlighted at high risk of selection bias (Hasunuma et al., 2016, Lindgren et al., 2013). The negative associations reported by Gehring et al. (2002) and Mölter et al. (2014b) were not confirmed in their follow-up studies in the same subjects (Morgenstern et al., 2007, Gehring et al., 2015b).

Overall, there was significant variability in the definitions of the '*asthma'* outcome, TRAP exposure assessment methods and the selection of and adjustment for confounders. TRAP exposure was most commonly assessed by LUR models. NO_2 was the pollutant most studied, followed by $PM_{2.5}$, $BC/PM_{2.5\ absorbance}$ and PM_{10}. In studies employing LUR modelling to estimate TRAP, there was evidence that the models' validity differed across pollutants with LUR models capturing variability in mean BC and NO_2 concentrations best whilst being less adequate in estimating mean $PM_{2.5}$ concentrations. TRAP exposures were almost exclusively assigned to the participants' residential addresses, with a few exceptions. Very little work has been done to incorporate exposure differences due to children's' mobility, where relevant.

Overall and age-specific meta-analyses were conducted by pollutant, pooling the most homogenous, conservative and robust risk estimates. In the meta-analyses, statistically significant random-effects risk estimates were estimated in association with the exposure to BC, NO_2, $PM_{2.5}$ and PM_{10}. Sensitivity analyses excluding the study that contributed to the largest weight (the smallest SE); excluding case-control and cross-sectional studies and excluding studies with special characteristics that might compromise the generalizability of findings supported the key findings and conclusions. Across the overall meta-analysis and the age-specific analysis, the least heterogeneity was seen for the BC estimates, little heterogeneity for the $PM_{2.5}$ and PM_{10} estimates and the high heterogeneity for the NO_2 and NO_x estimates. There was some suggestion of sex differences and differential effects of TRAP by the asthma phenotype being studied.

2.5.2. Strengths

Thus far, this is the largest and most up-to-date review and analysis of current evidence of the aetiology of childhood asthma and TRAP. The key strengths of this study are its large coverage alongside its in-depth, transparent and reproducible evaluation of the evidence from studies particularly focused on TRAP exposures as a potential cause of childhood asthma.

This study is also a timely contribution to a rapidly evolving field which could inform the focus and design of future research, to improve its utility. Further, meta-analyses were conducted enabling exploring the association with the different pollutants and the drivers of heterogeneity. Age-specific meta-analyses were conducted in this study for the first time exploring differences in the risk estimates and heterogeneity between the different age groups.

2.5.3. Limitations

Despite its strengths, the approach also has its limitations.

In the meta-analysis, results were solely derived from continuous exposure analyses in the individual studies. Continuous exposure analysis is based on the notion of a natural log linear relationship between the exposure and the outcome, which may not be the case in the TRAP-asthma associations, although this was assumed. The main reason for using continuous exposure analyses results was that these were largely available across the included studies whilst, on the other hand, studies reporting high versus low exposure analyses were very few and of limited power restricting their usability. In line with the systematic review's inclusion criteria, all the included studies have specifically investigated ‘traffic-related’ air pollution metrics and/or established traffic-related air pollutants, yet only a few (7 or 17%) used air pollution dispersion models, starting the analysis from source (vehicle emissions) to the health effects (childhood asthma), and hence the specific effects of traffic sources cannot be completely distinguished from the effects of other sources, with confidence. An assumption underlying this systematic review was that childhood and early-life represent the most critical exposure windows for the development of asthma in relation to TRAP. As such, precedence in the meta-analysis was always given to the risk estimates that related to the earliest exposure window (e.g. birth address exposures were selected instead of current/later address exposures). Although there is ample evidence to support this assumption (Section 2.2.), it can also be that exposures in later life contribute to the development of asthma, but this was not investigated. Also, in line with the inclusion criteria, estimates and studies pertaining to prenatal exposures were excluded (Clark et al., 2010, Sbihi et al., 2016, Deng et al., 2016, Liu et al., 2016), and although this may be an artificial distinction as birth year exposure may well be correlated to prenatal exposures, the conceptual framework of this systematic review required the child’s own exposure for inclusion.

In the age-specific meta-analyses, ‘school-age’ (i.e. 6 years old) was used as the cut-off age to categorize study results. This approach did not allow exploring potential differences in the effects of TRAP on asthma between pre-pubescent and pubescent children as the range > 6 years old included both groups. In the underlying data contributing to the meta-analysis, there was some of lack of equivalence among the exposure measures, populations and ‘asthma’ definitions studied. Yet, the steadily increasing number of studies within the field, much of which are conducted using LUR models and in the same populations at different follow-ups, alongside the recent availability of new studies using harmonized methods (Gehring et al., 2015b, Mölter et al., 2014b), were considered good reasons to justify a meta-analysis approach. Several hypothesis-driven sensitivity analyses, retaining studies that are most alike and more robust, were conducted and supported the main findings and conclusions. Due to the variability across studies, these findings need to be explored in future analyses when more studies become available. Future synthesis would also benefit from greater standardization of study methods, although some differences are inevitable, especially considering the current indistinct definition of asthma.

2.5.4. Meta-Analysis Interpretation, Studies Quality and Heterogeneity

Further points which warrant discussion emerged from this study. There was a focus on studying NO_2 effects which is likely to be related to the wide availability of this pollutant measure and its relative specificity to TRAP (Favarato et al., 2014). There also is a focus on NO_2 in air quality guidelines, plans and mitigation strategies, whilst less attention is generally given to the other pollutants. In recent years, there appeared to be a shift from studying standard air pollutants to studying other agents including black and elemental carbon, particulate matter composition elements and other properties such as oxidative potential. Yet the number of studies on these other pollutants is still small. The meta-analyses were only possible to conduct for BC, NO_2, NO_x, $PM_{2.5}$ and PM_{10} and there was variability in the numbers of studies contributing to the meta-analyses for the different pollutants (Table 3). The results showed that the meta-analyses for NO_2, which had the highest number of studies, produced the highest heterogeneity and a relatively small effect size, which may indicate that NO_2 may not be the putative agent in the TRAP mixture, but may act as a surrogate for BC or $PM_{2.5}$, for example, which showed less heterogeneity, or for other unmeasured pollutants. Results from the $PM_{2.5}$ meta-analyses, where 10 studies were available, were also relatively low in magnitude but had less heterogeneity. In particular, when excluding the high risk birth cohort by Carlsten et al. (2010), where $PM_{2.5}$ could act as an adjuvant for transporting allergens deep in the lungs of predisposed children, the random-effects model estimated no heterogeneity. The results of the meta-analyses for BC and $PM_{10,}$ where there were 8 and 12 studies, respectively, produced higher effect sizes and minimal heterogeneity, and these findings were robust in sensitivity analyses, more so for BC. Finally, only 7 studies were available for NO_x, and although the overall risk estimate was high in magnitude, it did not reach statistical significance and there was suggestion for publication bias as indicated by the funnel plots' asymmetry. Given the smaller number of studies available for pollutants other than NO_2, the power to detect heterogeneity and associations was limited and further analysis is needed to support findings and assertions.

As there is evidence that the accuracy of asthma diagnosis might differ according to the child's age and that younger children might outgrow their asthma symptoms at older ages (Martinez et al., 1995), age-specific meta-analyses were conducted with a cut-off age of 6 years when asthma is diagnosed more readily. This reduced the number of applicable studies and with such small numbers, interpretation should be cautious. In the age-specific meta-analysis, the overall risk estimate of $PM_{2.5}$ in the younger age group lost its statistical significance, which could be attributable to the reduction of power, but all other risk estimates remained significantly increased. Generally, the effects seemed to be higher in the younger age group. The heterogeneity in both the $PM_{(2.5,10)}$ analyses and the BC analysis was reduced in the older children as compared to the overall and to the younger children analyses; a trend that was previously suggested to imply differences in susceptibility between children at a younger age, which attenuated over time (Gehring et al., 2015b). Future meta-analyses, when more studies become available, could explore effects and heterogeneity at different age cut-off points. The design of this systematic review (cut-off age at 18 years old), and the current evidence base, did not allow for further exploration regarding whether the detected associations persist at older ages.

Although the overall meta-analysis showed positive and statistically significant associations with the 4 pollutants examined, these pollutants are highly correlated in traffic exhaust and the overall risk estimates cannot be conclusively interpreted as a certain pollutant's effect. In fact, as mentioned above, the high heterogeneity estimated in the NO_2 and NO_x analyses, in line with other studies (Mölter et al., 2014b), may suggest that these pollutants are surrogate for another pollutant or mixture responsible for the observed effects such as BC or $PM_{2.5}$. However, the number and quality of studies differ which makes it difficult to draw definitive conclusions. Pollutants like BC and PM_{10} are considered to act as tracers of older diesel, particularly heavy-duty traffic emissions which are typically not equipped with engine control and exhaust after-treatment systems such as diesel particle filters, so their emissions of larger, heavier particulate matter are higher. The morphology of these larger particulates can include un-burnt hydrocarbons held hydroscopically between carbon/BC. BC has been shown to be highly correlated with EC too (Cyrys et al., 2003) but importantly with other species known for their toxicological potency (Li et al., 2003a, Li et al., 2003b), like polycyclic aromatic hydrocarbons, benzene and volatile organic compounds (Fischer et al., 2000, Karimi et al., 2015).

Several other possible factors can explain heterogeneity identified between the studies. Firstly, there were differences in methods used to identify asthma cases, with the most commonly employed method being parental-reporting of doctor-diagnoses. Some of the heterogeneity detected therefore might be due to regional differences in doctors' practices. Other methods employed to assess asthma varied across the remaining studies making their estimates more difficult to compare. As for the quality of these estimates, recall and reporting bias remains a concern in parental-reporting of doctor-diagnoses. The extent by which asthma estimates were captured by these different methods was not discussed much in this literature, but there are examples of the poor overlap and significantly different estimates one obtains utilizing different approaches. For instance, a Danish study of > 50,000 children showed that asthma prevalence from parental-reporting of doctor-diagnoses, diagnoses from hospitalization registries and medication data from prescription registries, varied substantially with poor agreement (Hansen et al., 2012). Further assessment of the nature of disease misclassification due to the above factors and its effect on exposure-response associations is yet needed.

Secondly, the different levels of exposure, and constituents of air pollutants in the different areas may explain differences between studies. The different models used to assess TRAP exposures could also result in further heterogeneity. Most studies using LUR models showed consistently increased risk of TRAP-associated asthma. Although exposure indices from LUR models were considered relatively robust in capturing small-area variations of TRAP in comparison to the other models, it was of note that LUR may introduce an exposure misclassification by pollutant. Whilst NO_2 and BC can be truly considered as traffic-related and primarily exhaust pollutants (Krämer et al., 2009, Cyrys et al., 2003, Fischer et al., 2000), $PM_{2.5}$ is primarily a non-exhaust pollutant and has other important local (traffic and non-traffic), regional sources and secondary particle formation mechanisms which are not encompassed in the geographic variables founding typical LUR models. The fact that the encountered LUR models were not as accurate in capturing $PM_{2.5}$ concentrations is therefore relevant in this debate and potential for more downward bias due to the less robust regression models in the case of $PM_{2.5}$ is expected (Basagaña et al., 2013). Studies using monitoring stations data were consistent in demonstrating increased risks. However, given that most network monitors are usually located to measure urban or regional background air pollution (Yamazaki et al., 2014), these studies are less specific to traffic, fail to account for TRAP spatial variability, and by definition, introduce an inevitable mismatch between the stations' and subjects' locations (Kaur et al., 2007). This affects the confidence in the PM_{10} meta-analyses results where 7 out of the 12 studies included used fixed-site monitoring stations. Finally, results from studies using dispersion models were inconsistent. Studies have suggested that dispersion models systematically under estimate TRAP concentrations at the roadside and in congested areas, a problem attributable to inputting these models with unrealistically low vehicle emission factors, especially for NO_x and NO_2 (Williams et al., 2011). Furthermore, the unusually high exposure estimates that occur in canyonised streets (Longley et al., 2004, Vardoulakis et al., 2003) were only captured in one study using a street canyon module (Gruzieva et al., 2013). Unfortunately, due to the limited number of studies, it was not meaningful to formally assess whether the type of exposure model explains part of the heterogeneity between studies.

There were numerous positive and near-statistically significant associations encountered which may well indicate a lack of power, or a heterogeneous effect amongst certain subgroups which was diluted within the aggregated population. In this context, an open question is whether the exposure to TRAP is really associated with the development of non-atopic asthma only. This study, as well as results from studies showing that exposure to traffic pollutants is primarily associated with non-atopic wheeze (Nordling et al., 2008) and that children with no parental history of asthma are at higher risks of TRAP-associated asthma (McConnell et al., 2010, Nishimura et al., 2013, Gordian et al., 2006), support this notion, yet more data is needed. In the light of the recent scientific consensus that asthma is not a single disease entity (Corren, 2013, Wenzel, 2012) and the mounting evidence that atopy is much less relevant in asthma pathogenesis than previously believed (Asher, 2011), it seems that research within the field is lagging behind in attempting to address this detail. If the exposure to TRAP was associated with one asthma phenotype only, then syncing the risk estimates for all phenotypes in one value is misguided and would distort the detected associations. Heterogeneity could also be driven if there was a differential susceptibility to the respiratory effects of TRAP by sex. Separate analyses for females and males were again only available for a very limited number of studies.

Finally, as there is wide inter-individual variability in responses to air pollution (Brunekreef and Holgate, 2002), genetic variations could explain some of the observed heterogeneity. This was only investigated by Kerkhof et al. (2010) and MacIntyre et al. (2014a) who found that toll-like receptor genes responsible for activating the innate immune system, and variant GSTP1 genotypes which code for an enzyme that metabolizes reactive oxygen species; influence the susceptibility to effects of TRAP on asthma (MacIntyre et al., 2014a, Kerkhof et al., 2010).

2.5.5. Avenues for Future Work and Next Steps

Based on this updated evidence base, it was concluded that there is now sufficient evidence to support an association between the exposure to TRAP and the development of childhood asthma. The high degree of consistency in findings and conclusions of the individual studies, the results of the meta-analysis and associated sensitivity analyses, and considerable support from the existing literature reinforce the hypothesis that childhood exposure to TRAP contributes to their development of asthma. Yet, many questions remain open including: which are the putative agents in the TRAP mixture? what is the specific contribution of traffic to ambient air pollution and the excess risk detected? which vehicle fleets are most worrisome and where/how to intervene? what is the accuracy and precision of the health effects estimates? is the increase in asthma incidence and/or lifetime prevalence estimated represents added cases, an acceleration of the development of asthma or increased severity making the disease sufficiently apparent for clinical diagnosis? And what are the public health impacts of the detected associations on a population scale?

Future meta-analyses would benefit from greater standardization of study methods including exposure assessment harmonization, outcome harmonization, confounders' harmonization and the inclusion of all important confounders in the individual analyses (e.g. socioeconomic status, exposure to environmental tobacco smoke and heredity). Future synthesis could also explore different exposure windows comparing effects of early life to later childhood exposures and possibly prenatal exposures. Other specific recommendations that would help improve the utility of new research in this field are summarized in Figure 10.

Subsequent work of this thesis will be of empirical nature, building on lessons learnt from this synthesis and furthering some areas of inquiry in the field including: using air pollution dispersion models to estimate the contribution of TRAP to ambient air pollution and distinguish effects of TRAP from other sources, including NO_x in the analysis and estimating the local burden of childhood asthma attributable to TRAP using different air pollution assessment methods including full-chain models combining traffic, emissions and atmospheric dispersion models and, alternatively, a commonly used LUR model. The focus will be on the year 2009 in Bradford, when traffic, meteorological data and the LUR model was available.

1. Systematically reporting categorical exposure analysis, alongside continuous exposure analysis
2. Systematically investigating associations with multiple exposure windows
3. Using air pollution dispersion models or equivalent methods (e.g. source apportionment models) to distinguish effects of TRAP from other sources
4. Expanding the focus on NO_2 to other traffic-related pollutants including BC, NO_x, PM, ultra-fine particles and particles constituents
5. Assessing the effects of co-/multi-pollutants
6. Exploring effects and heterogeneity at different age cut-off points, distinguishing between pre-pubescent and pubescent children and undertaking follow-up studies in the same populations
7. Expanding the methods of asthma assessment beyond reporting of doctor-diagnosis (e.g. using prescribed medication from prescription registry or diagnosis codes) and attempting to validate the asthma outcome measures
8. Assessing the nature of disease misclassification due to different asthma definitions and its effect on exposure-response associations
9. Systematically reporting bias concerns and attributes on study quality and performing adjustments where necessary
10. Formally assessing whether the type of exposure model explains part of the heterogeneity in effects (e.g. by meta-regression or meta-analyses specific to the exposure models)
11. Systematically investigating differences in the associations between sexes
12. Systematically investigating differences in the associations between different phenotypes and distinguishing between family history of asthma and family history of atopy/allergies

Figure 10 Recommendations for Future Research on TRAP and Childhood Asthma

3 Vehicle Traffic Network Modelling

3.1. Background

As it is unfeasible to collect/observe information on traffic activity (e.g. traffic flows and average speeds) on all roads in a study area, traffic activity is often estimated by modelling the road network and trips occurring on it. Emerging traffic measurement techniques such as remote sensing (Toth et al., 2003, Holt et al., 2009), satellite imaging and air photos (McCord et al., 2003, Larsen et al., 2009, Wang et al., 2016b), and telematics (Pellecuer et al., 2016), can provide observed traffic activity data at a finer spatial and/or temporal scale when compared to traffic models, but these methods are as yet developing and were not available in Bradford at the time of this work.

In this study, traffic activity, including traffic flows and speeds, was estimated using transport modelling which was chosen over using measured traffic flows from traffic counters, as was done in a previous relevant study in Bradford (de Hoogh et al., 2014). This was because traffic counters were limited in number and geographical coverage, providing incomplete spatial sampling (Figure 11). In an exposure and health impact assessment study, as in the present study, a high spatial coverage of roads in the study area, possible to obtain by transport modelling techniques, was considered of importance to capture the levels and spatial variability of air pollution exposures. Furthermore, traffic counters only record traffic flows (and sometimes traffic speeds) at the counters point locations which could be problematic depending on the location of the counter in relation to exits and entries of the road link and other special characteristics of the link (e.g. the presence of a shop or a facility). When traffic speeds are not recorded at the counter locations, speed limits at the corresponding roads are sometimes used (de Hoogh et al., 2014) to represent the average traffic speeds necessary for subsequent emissions estimation (Chapter 4). Assuming speed limits as the average traffic speed is, however, unrealistic and disregards effects of congestion and the fact that speed limits are often not achieved in urban areas and all driving conditions, which has impacts on the accuracy of emission modelling (Chapter 4). Finally, although aggregate traffic counts at regional and national levels are considered robust, this is not the case for traffic counts at the local level, which are the focus of this study (Department for Transport, 2015a).

Aggregate traffic counts at the regional and national levels are dominated by motorway and larger roads traffic where traffic flows are often in free flow and detectors are reliable. Conversely, in urban settings, stop-start driving is common and separation distances between vehicles are small making detectors less reliable.

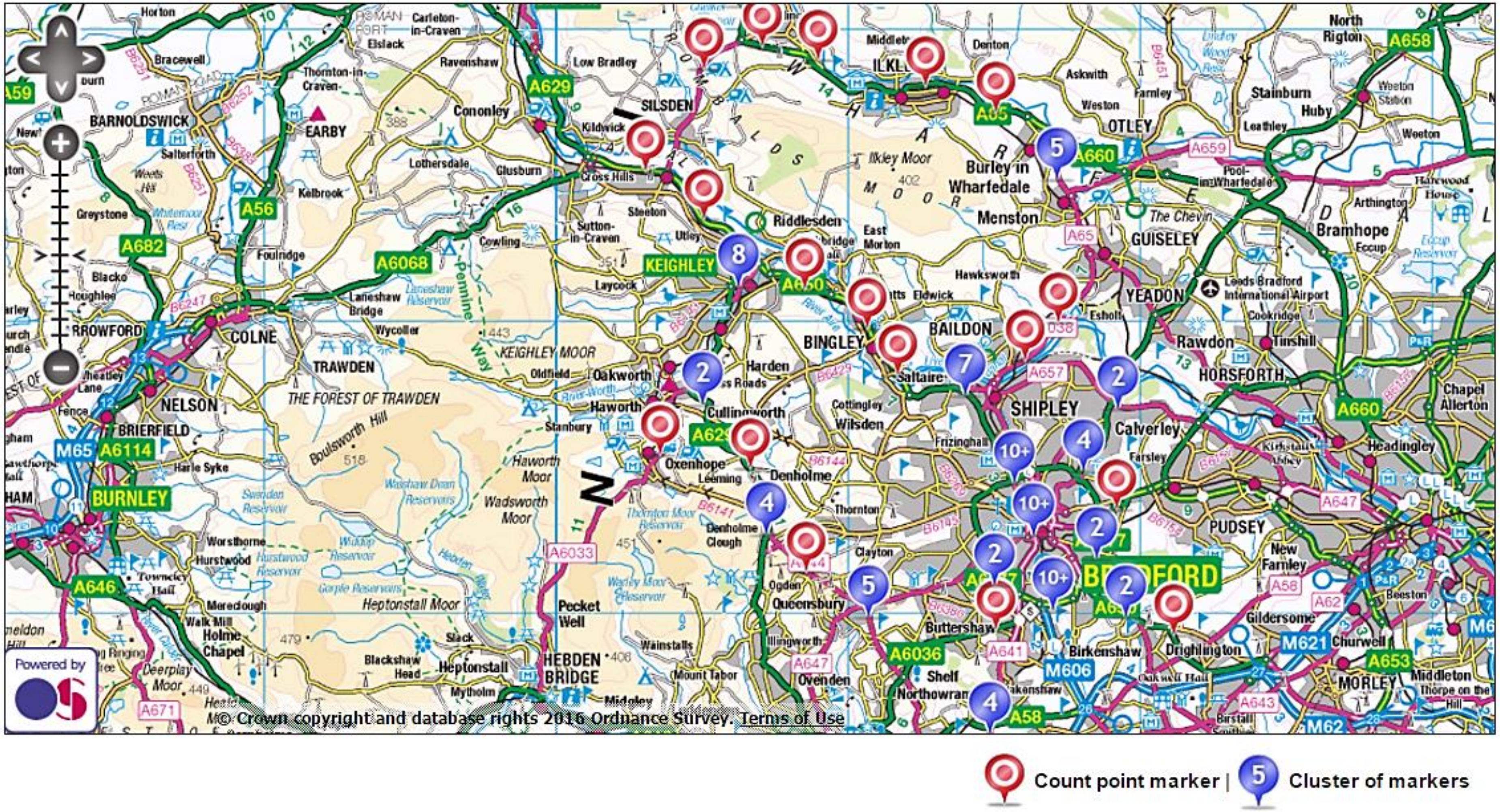


Figure 11 Bradford's Traffic Count Points in 2015 (N=109 count points), Source: Department for Transport (2015a)

In transport modelling, a model is a combination of network data, which is a mixture of origin (place where the trip started) and destination (place where the trip ended) zones, road links connected to each other by nodes and the traffic data included in the origin-destination matrices. The traffic data represents the travel demand to and from each zone included in the model. An origin zone could be for e.g. a residential area producing trips to destination zones for e.g. office developments, a university, shopping centre etc., which attracts trips. Conventional transport models run in four stages, as shown in Figure 12.

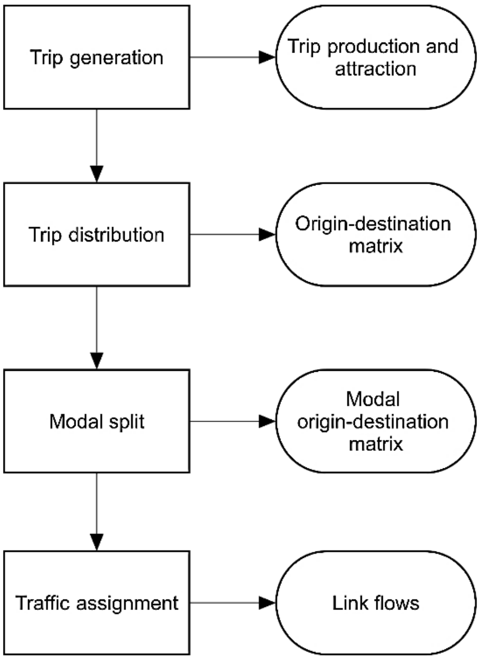


Figure 12 Traditional Four Step Transport Modelling, Source: Own Work (NCH Software)

Trip generation involves the generation of trips from an origin zone and their attraction to a destination zone in the network; trip distribution involves distributing where the generated trips go and where the attracted trips come from and producing an origin-destination matrix which is then used in the final traffic assignment model; modal split involves splitting the trips by transport mode based on the cost of travel and traffic assignment involves choosing the trip routes and loading the origin-destination matrix onto the network's links, producing link flows (Timms et al., 2016). Typically, transport models only result in data (traffic flows and average speeds) modelled over peak periods e.g. AM peak and/or PM peak hour. In this study, traffic modelling was carried out using the Simulation and Assignment of Traffic to Urban Road Networks model (SATURN), which is the most common traffic model used by local authorities in the UK and the only model available for Bradford.

3.2. Chapter Objectives and Contribution to Literature

The objective of this research phase was ***to obtain, run and independently validate a previously developed SATURN traffic model for the City of Bradford to estimate traffic flows and average traffic speeds in the study area and obtain the physical characteristics of the road network including the road lengths and geographical locations,*** *in preparation for subsequent emissions and air pollution dispersion modelling*. As will be shown later, the quality of the legacy, (large and complex) SATURN traffic model was substandard as the model turned out to be a schematic representation of the road network, which was not correctly geo-referenced (in terms of road positions and road curvatures). An attempt to correct the locations of the roads in the geo-coded traffic network was undertaken. Further, an independent validation exercise and the scaling of the modelled traffic flows over the day period for more accurate daily air pollution dispersion estimation was undertaken. This research phase provided traffic flows and average traffic speeds at each hour of an average weekday and weekend, which will feed into a newly developed and a standard emission model for Bradford (Chapter 4), and subsequently into air pollution dispersion modelling (Chapter 5), which will be undertaken to estimate the air quality profile, the childhood population exposure to TRAP and the associated burden of childhood asthma within Bradford.

3.3. Methods

The overall methodology used in this research phase to derive the average traffic speeds and traffic flows and classes on the Bradford road network is illustrated in Figure 13, and presented in detail next.

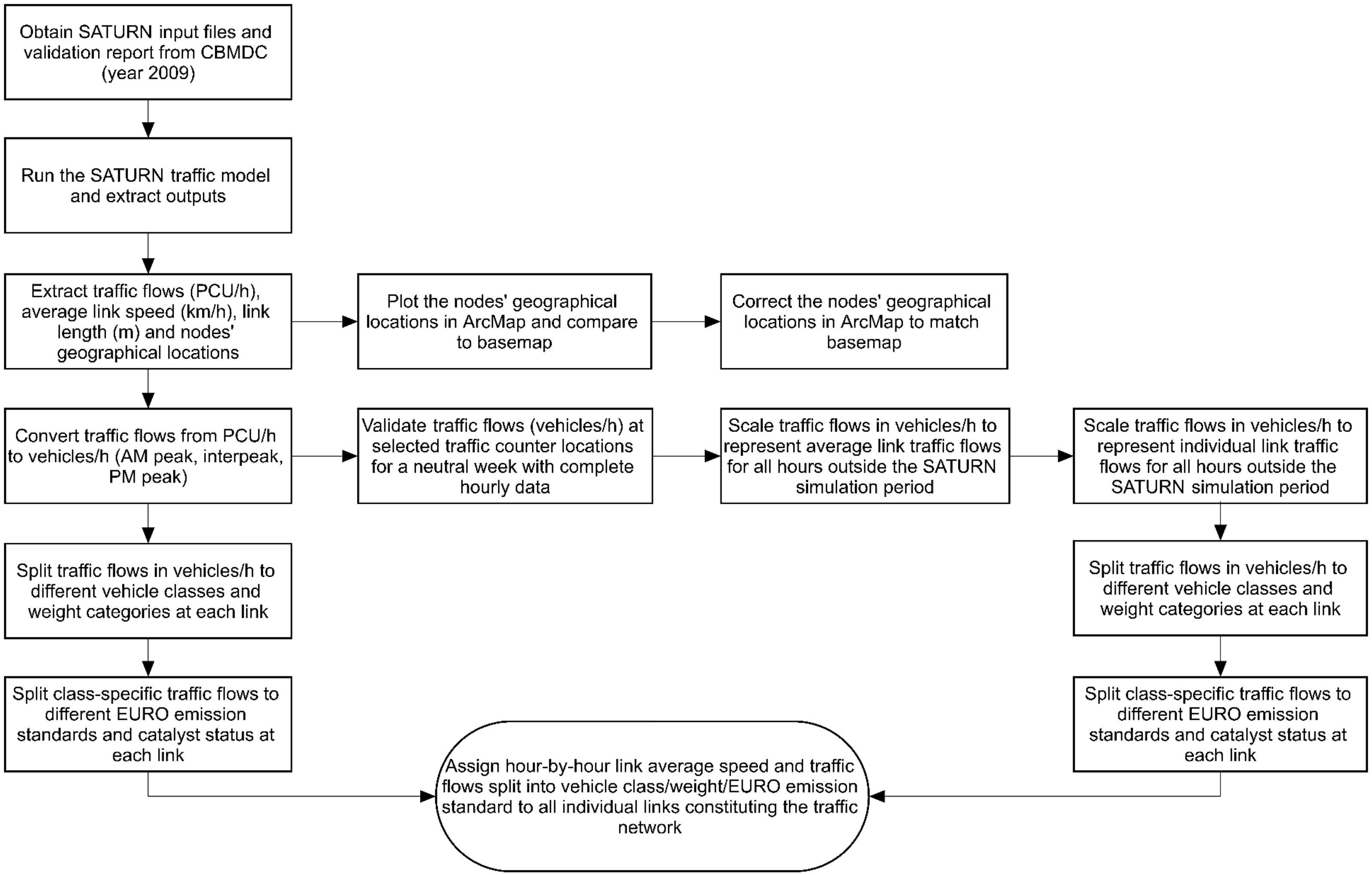


Figure 13 Traffic Activity Estimation Overall Methodology, Source: Own Work (NCH Software)

3.3.1. Traffic Modelling using SATURN

SATURN is a suite of road network analysis programs which have been developed through the Institute for Transport Studies at the University of Leeds, and distributed by Atkins Limited, since 1982. SATURN has over 300 users worldwide (Namdeo et al., 2002), and is perhaps the most commonly used transport modelling software in the UK where many local authorities, including the City of Bradford Metropolitan District Council (CBMDC), employ it for transport planning purposes. Overall, SATURN models across the UK are an important part of the transport decision-making processes. There are six basic functions of SATURN, as follows (SATURN Manual, 2015):

1. a combined traffic simulation and assignment model for the analysis of road-investment schemes;
2. a 'conventional' traffic assignment model (with or without simulation) for the analysis of large networks;
3. a simulation model of individual junctions;
4. a road network editor, data base and analysis system;
5. a matrix manipulation package to produce, e.g. trip matrices.
6. a trip matrix demand model covering the basic elements of trip distribution, modal split etc

In this study, the SATURN model is used for its function 2; as a traffic assignment model, with simulation, for the analysis of the urban Bradford road network. The spatial coverage of the SATURN modelled network was considerably wider (4,500 links) than the spatial coverage of the traffic count points available in Bradford in the year 2009. The traffic counters available were as follows, and most of these had significant missing data:

- 109 Department for Transport traffic counters, reporting annual average daily traffic flows (Department for Transport, 2015a); and
- 138 local (council operated) automatic traffic counters reporting annual average daily traffic flows and hourly traffic flows (Ahmad, 2016).

3.3.2. SATURN First Principles

SATURN is a traffic modelling suite that includes two interlinked models: a 'simulation model' of individual junctions, as well as an 'assignment model' for the whole road network. These two models interact within the suite to give a more detailed and realistic representation of traffic behaviour at junctions and on the overall road network thereafter (SATURN Manual, 2015). The modelling process within the suite starts with the assignment model which requires two inputs from the user:

1. A road network (supply); and
2. A trip matrix (demand)

The road network specifies the physical structure of the roads upon which trips occur (e.g. the link lengths, link capacities, geographical locations). The trip matrix specifies the number of trips from zone *i* to zone *j,* for all zones included in the traffic network. Both the road network and the trip matrix are the inputs to a route choice model. Trips are allocated to routes based on the route choice model, and the total flows along road links and the corresponding network costs (e.g. travel times or average generalized cost) are calculated. Once the assignment is carried out, the user can view and analyse the model's outputs. The structure of the (SATURN) traffic assignment model is illustrated in Figure 14.

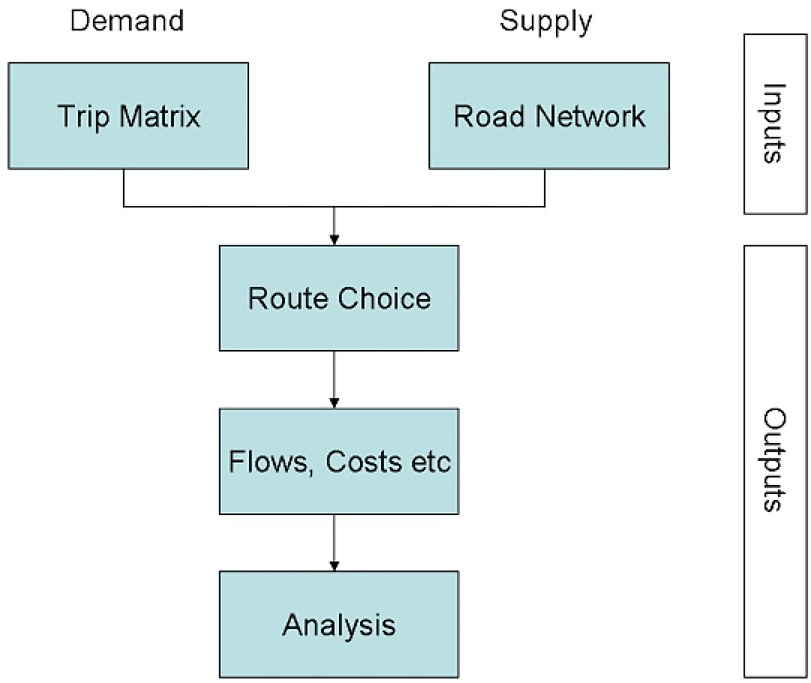


Figure 14 General Structure of an Assignment Model, Source: SATURN Manual (2015)

After the first round of traffic assignment, the simulation model takes the road link allocated traffic and creates another more accurate cost-flow relationship by working out the delays that will occur at the network's junctions due to the assigned flows. As such, the simulation model provides a more detailed representation of what is happening at each junction in the network considering (1) additional delays that road users turning on roads may suffer compared to those driving straight ahead and (2) the ability of cars to get out at a give-way junction depending on the availability of gaps in traffic going past. The result is a closer estimation of cost-flow relationships, which are then passed back to the assignment model, allowing a second set of routes to be allocated (SATURN Manual, 2015, Traffic Network Models, 2015).

This iterative process is referred to as the 'assignment-simulation loops' (Figure 15). The loops are essential because the simulated turn-based flow-delay curves that are initially passed to the assignment model are only approximations, which disregard the interactions between the network's links while determining delays. Several sources of interactions exist between links, including shared lanes, signal optimization and co-ordination, merging and weaving, etc., and these are considered in the subsequent assignment and simulation loops.

The loops between the assignment and simulation are iterative and keep running until the model 'converges'. Model convergence occurs when all the routes stabilize, and reasonably steady flows are obtained. This is judged by calculating the changes in flow relative to the previous loop; values of which need to be very small (e.g. < 5%). When the link flows difference between loop n and loop n-1 is less than e.g. 5% (user specified value), the model converges, and the assignment-simulation loops stop. The user is provided with output data which can be exported and analysed (SATURN Manual, 2015, Traffic Network Models, 2015).

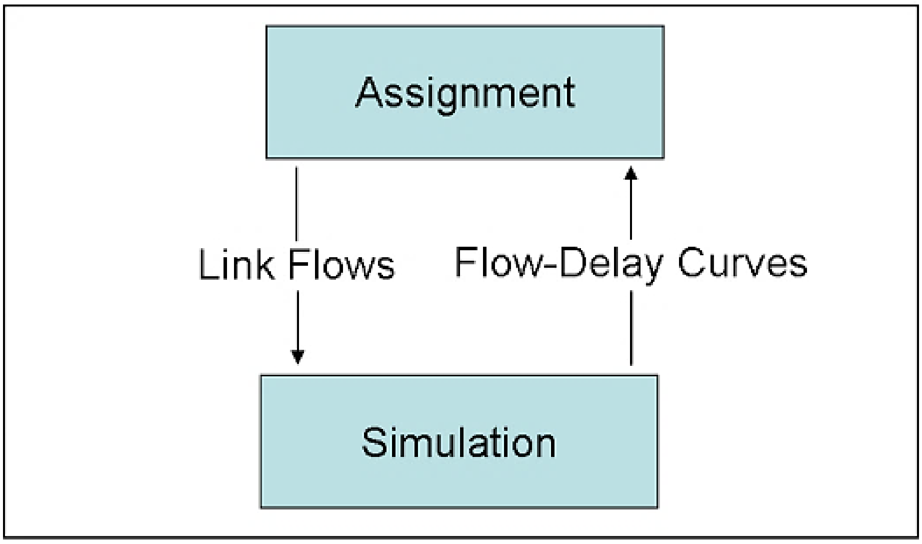


Figure 15 The Simulation-Assignment Loop, Source: SATURN Manual (2015)

3.3.3. Validation of Traffic Models and the SATURN Model

A model's calibration involves any model adjustments carried out to reduce the differences between the modelled and observed traffic data. A model's validation involves comparing the modelled traffic data (e.g. traffic flows and traffic average speeds), to the observed traffic data which ideally have not been used in the model's calibration.

For the validation, the differences between the modelled and observed data should be quantified and assessed against some established criteria. The acceptable proportions of instances where the assessment criteria are not met are defined in traffic modelling guidance and should be assessed as part of the model's validation. In the UK, the validation criteria and acceptability guidelines for a traffic assignment model are given in the Department for Transport (DfT) TAG unit M3.1 (Department for Transport, 2014). The criteria and guidelines given in this document are similar to those in the UK Design Manual for Roads and Bridges (DMRB) (The Design Manual for Roads and Bridges, 2012) and are widely used in the practice for the validation of traffic models. The traffic model's validation includes:

1. a comparison of the modelled (assigned) flows and observed flows (counts) (as a check on the quality of the assignment); and
2. a comparison of the modelled and observed (surveyed) journey times (as a check on the quality of the network and the assignment).

For link flow validation, the following two measures should be used. These measures are considered broadly consistent and link flows, which meet either criterion, are considered satisfactory:

1. the absolute and the percentage difference between the modelled and the observed flows; and
2. te Geoffrey E. Havers (GEH) statistic which is a modified Chi-squared statistic that considers differences between the modelled and observed traffic flows (Lee et al., 2012). The GEH statistic can be calculated as follows:

$$\mathrm{GEH} = \sqrt{\frac{2(\mathrm{M}-\mathrm{C})^2}{\mathrm{M}+\mathrm{C}}} \ldots \text{Equation 3.1.}$$

Where M is the hourly 'modelled' traffic flow and C is the 'observed' traffic flow.

The validation criteria and acceptability guidelines for the link flow validation differ depending on which validation measure was used, as follows (Department for Transport, 2014, Steer Davies Gleave, 2009):

- **Using criteria/measure 1:** For flows < 700 vehicles/hour, >85% of cases should have individual flows within 100 vehicles/hour of counts

- **Using criteria/measure 1:** For flows from 700 to 2,700 vehicles/hour, >85% of cases should have individual flows within 15% of counts
- **Using criteria/measure 1:** For flows > 2,700 vehicles/hour, >85% of cases should have individual flows within 400 vehicles/hour of counts
- **Using criteria/measure 2:** >85% of cases should have individual flows with a GEH < 5.0. For traffic modelling work, a GEH of less than 5.0 is considered a good match between the modelled and observed hourly traffic flows.

For journey time validation, the percentage difference between the modelled and the observed journey time is used as the validation measure, and this is subject to an absolute acceptable maximum difference. The validation criteria and acceptability guidelines in traffic modelling dictates that >85% of cases should have modelled journey times that are within 15% of the observed times, or within 1 minute if higher than the 15% limit (Department for Transport, 2014).

in particular, the SATURN model has been extensively validated since its initial development in the 1980s (Gulliver and Briggs, 2005). The following paragraphs overview numerous studies which validated SATURN.

In a model validation report produced for Chelmsford, UK (Wiffen, 2009), the SATURN model was found to successfully conform to the model validation criteria, given in the DMRB. The model had all or almost all of cordons and screenlines with GEH< 4, 85% of cordon and screenline counts with a GEH < 5 (AM: 88%, PM: 86%), 85% of journey time routes < 15% or under the one-minute difference (AM: 81%, PM: 92%). When the comparisons were presented separately for each modelled period, the exception of compliance was in the AM peak journey time validation which only had 81% of journey time routes < 15%, but even this was very close to the DMRB 85% criteria. Other UK cities using the SATURN model have undertaken similar validation exercises; the results of which are concordant with the above study (AECOM Transportation, 2011, JMP Consultants Ltd, 2008, Cheshire East Council Highways, 2013).

Published studies also support the use of SATURN in traffic modelling. An early SATURN validation exercise was described in Matzoros et al. (1987). This was conducted in Manchester, UK, to assess SATURN's capability to predict likely impact of a city centre pedestrianization scheme that involved road closures. The tests were conducted for the city centre network, with a radius of approximately 3 km. For 73 links, not used in the calibration of the model, observed-estimated link flows were within 7.8% to 16.3%, depending upon flows in the surrounding buffer network, and generalized costs used in the assignment procedure. Following the road closure scheme, the modelled link flows were within 12% of the observed flows. These results were considered very good, considering that there was a 10% uncertainty in the observed vehicle count (Matzoros et al., 1987, Namdeo et al., 2002). On the other hand, journey times were estimated within one standard deviation of observed times, a less accurate estimate in absolute terms, but acceptable at the aggregate level. This lower degree of accuracy in estimating journey times was attributed to the great sensitivity of travel times to delays at the junctions when the network is near capacity.

Another validation exercise from Northampton, UK was described in Gulliver and Briggs (2005). In this study, hourly traffic counts made using pneumatic pressure loops at one site were compared to SATURN modelled flows over 24 hours at the same site. Results showed good agreement but the model overestimated morning and night flows (results were only presented graphically as shown in Figure 16).

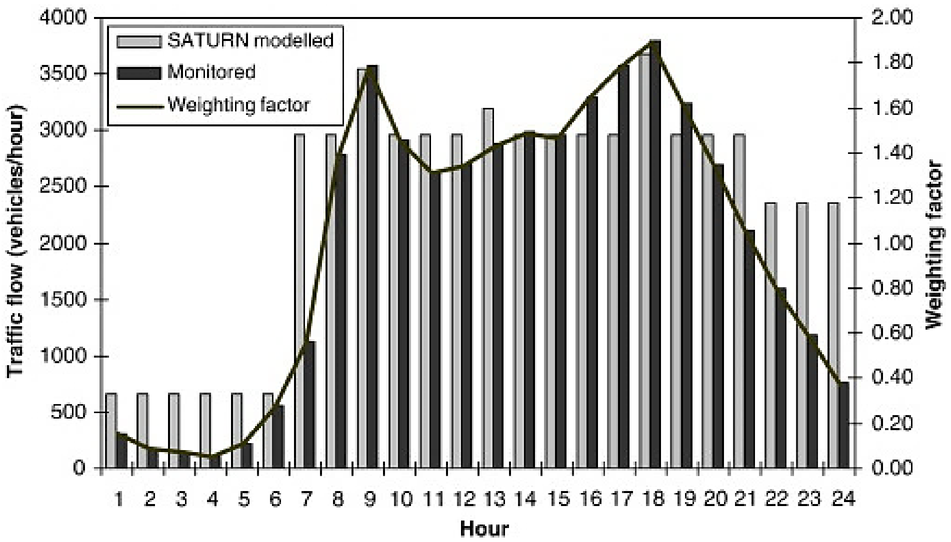


Figure 16 Monitored and Modelled Traffic Flows (Main Through-Route) and Derived Hourly Weighting Factors, Source: Gulliver and Briggs (2005)

3.3.4. Bradford SATURN Model: Inputs, Outputs and Validation

A SATURN traffic model covering the Bradford District was initially developed in 2001 by the consultancy Atkins Transport Planning (http://www.atkinsglobal.co.uk/en-GB/group/sectors-and-services/services/transport-planning), and was subsequently updated and validated against traffic count data in work by Steer Davies Gleave (http://www.steerdaviesgleave.com/), at the request of CBMDC in 2009 (Steer Davies Gleave, 2009). The input data files for this model were obtained from CBMDC and were used to provide traffic activity information in this study, which was focused on year 2009. The key input files obtained were the .UFS files which are the unformatted outputs from the simulation of three periods: AM peak, inter-peak and PM peak hour. The model obtained represented a large, city-scale, complex and validated traffic network model, which has been developed since 2001 by major transport planning consultancies. It was beyond the scope of this study to develop another version of this traffic model, and it was accepted as the core to the traffic modelling work.

In previous work undertaken by Steer Davies Gleave, the outputs of the obtained SATURN model were validated against an observed set of traffic counts and journey time data (Steer Davies Gleave, 2009), as will be described next. The traffic counts data set which was available for model calibration and validation consisted of 275 individual road links containing data from the AM and PM peaks, and 240 individual road links containing data from the inter-peak period. The averaging periods underlying this data was unclear and was not reported in the consultancy report (Steer Davies Gleave, 2009). As described above, the standard approach within highway modelling is to split the traffic counts data set into two distinct parts; one to be used in model calibration and an independent one to be used in model validation. Calibration links are used within the matrix estimation so that the model can adjust the flows in the matrix to the observed values. Validation links are not used in the matrix estimation and provide an independent subsequent check that the traffic flows estimated from the model are reasonably accurate. In this SATURN model, however, restricting the calibration and validation counts to two distinct data sets while attempting to limit excessive change to the old trip matrix (as defined by the XAMAX user specified value), resulted in the output statistics to fall below those that are set out by DfT/DMRB guidelines. Therefore, a series of five tests were devised and carried out to improve the model operation and output statistics (Table 4).

Table 4 Bradford Update Model (2001 to 2009)

Test	XAMAX[2] Value	Links used in calibration
1	2.5	All links except Outer Cordon and Screenline
2	2.5	All links
3	5.0	All links except Outer Cordon and Screenline
4	5.0	All links
5	5.0	All links excluding Screenline

[2] XAMAX is a user-set parameter that represents the maximum balancing factor used to limit excessive change to the old trip matrix

Table 5 displays the GEH output statistics for the validation links for all the model tests trialled and displayed in Table 4. The results for test 4, which included all available links data in the calibration of the model, resulted in the best match between the modelled and observed traffic counts. Although the PM peak statistic did not achieve the 85% DMRB threshold, it was very close in terms of both the GEH (Table 5), and DMRB criteria for individual link flow statistics (not shown). Ultimately, the model of test 4 was adopted, accepting a very good model calibration – as opposed to an independent flow validation.

Table 5 Bradford Highway Model- Output Statistics for GEH <5.0

Time	Test 1	Test 2	Test 3	Test 4	Test 5
AM	40%	77%	40%	88%	73%
IP	46%	89%	46%	95%	78%
PM	42%	73%	42%	82%	63%

As for journey times outputs, the validation was limited to the test of modelled versus observed journey times obtained for a total of 52 journey time routes within the area of the model. Unlike the traffic counts data, the journey time data available for validation were a wholly independent dataset which was not used to calibrate the model's link speeds or traffic behaviour. Table 6 displays a summary of the journey time statistics for test 4, which was the final model adopted. In line with DMRB guidance, the average difference between modelled and observed journey times was within ±15% for all time periods, although the individual modelled journey times showed higher variance. Overall, the differences between the modelled and observed journey times was that traffic travelled faster in the model, in all time periods. This suggested that roads capacity and/or speeds were over-represented in certain areas of the model and that it tended to under estimate congestion and/or special traffic-slowing incidences, particularly in the AM peak hour. The individual link output data and validation statistics for both traffic flows and traffic journey times for the AM peak, inter-peak and PM peak hour are given in the original validation report by Steer Davies Gleave (Steer Davies Gleave, 2009).

Table 6 Journey Time Route Summary Statistics

Statistic	AM peak	Inter peak	PM peak
Total modelled versus observed time	-15%	-8%	-7%
% routes within 5 minutes	88%	100%	88%

As there was relatively little detail on the techniques used in the above validation of this SATURN model and as the calibration links used so that the model can attempt to adjust the flows in the matrix to the observed flows were the same links used for validation (i.e. there was no independent validation data set) (Steer Davies Gleave, 2009), an independent validation exercise was undertaken by the author and is described next.

One neutral traffic week excluding weekends, public holidays and school holidays was selected for the validation purposes. This was the week (days) between 5 October and 9 October 2009. On any of these days, traffic is expected to behave similarly to any other weekday between March and October, excluding all public holidays and school holidays (Department for Transport, 2016a). There were 588 automatic traffic counters (ATC) with traffic flow data at some point in time in Bradford indexed in the CBMDC online database and traffic analysis software: DRAKEWELL (https://drakewell02.drakewell.com/). Access to DRAKEWELL was given by the CBMDC personnel and each traffic counter indexed in the database was accessed and checked for data availability between 5 October and 9 October 2009. Only counters with complete hour-by-hour traffic flows for all days between 5 October and 9 October 2009, were selected for the validation exercise to enable a consistent averaging period for hourly traffic and a meaningful comparison with modelled data. Further, the hour-by-hour traffic flows in the weekend of the same week (10 October and 11 October 2009) were extracted from the same counters.

Out of the 588 indexed ATC, only 19 ATC, reporting on 35 directions of traffic in Bradford, had complete hour-by-hour data in the selected week and weekend. Overall, significant amounts of data were missing. This data was manually extracted and tabulated. Each counter's location was then matched to the corresponding SATURN link by visually inspecting the map of the ATC locations and comparing it to the SATURN road network plotted in a GIS. At each counter, the AM peak hour (08:00-09:00), the first inter-peak hour (10:00-11:00) and the PM peak hour (17:00-18:00) hour traffic counts, averaged across the investigated week, were compared to the SATURN's output from each corresponding link, at each corresponding hour. The GEH statistic (Equation 3.1) was calculated for each link/ time included in the validation. The results of this exercise are described in Section 3.4.5.

The SATURN input files were read into SATURN, version 11.1.09. The model's geographical coverage/simulation extent is illustrated in Figure 17, with the central red boxed ring road representing Bradford's Ring Road (A6177), and the blue boxed area representing the study area. In this figure, rectangles, circles and squares (green, dark cyan, and red) are the simulation junctions; with the different shapes denoting the different junction types (priority junctions are represented by rectangles, roundabouts by circles, and traffic signals by squares). External nodes are represented by pentagons (purple), zones by triangles (turquoise), and all nodes by hexagons (grey) (SATURN Manual, 2015).

As mentioned, the model represented the traffic conditions of year 2009 and was based on a previous model established and validated by Atkins in 2001, which served as the baseline trip matrix for undertaking the 2009 update. The 2001 matrix was updated to 2009 levels by using recent traffic data collected between 2005 and 2009. The recent traffic data collected at multiple sites were used to provide localized growth factors where possible that were annually averaged when more than one years' worth of data was available at one site. Based on these growth factors, an extrapolation was made from the final year of the traffic count to year 2009. Where negative traffic growth was observed, the downward trend was assumed not to continue, and the traffic was kept static from the final year of observation. There were cases where traffic counts were only observed in one year precluding establishing an extrapolation growth factor. In these cases, assumptions were made on the level of growth based on the average traffic growth on similar road types.

Compared to the previous matrix of 2001, the updated 2009 matrix resulted in a slight increase of +3.1%, +2.6% and +1.0% in the traffic of the AM peak, inter-peak and PM peak trips (in vehicles), respectively. In comparison to traffic growth figures over this period based on independent data from the DfT, these results are reasonable, as Bradford's counted traffic has undergone positive but small increases between 2000 and 2009. The total number of vehicles on an average day at 109 traffic counters in Bradford increased by 2.12% between 2002 and 2009, as shown in Figure 18 (data extracted from Department for Transport (2015b)).

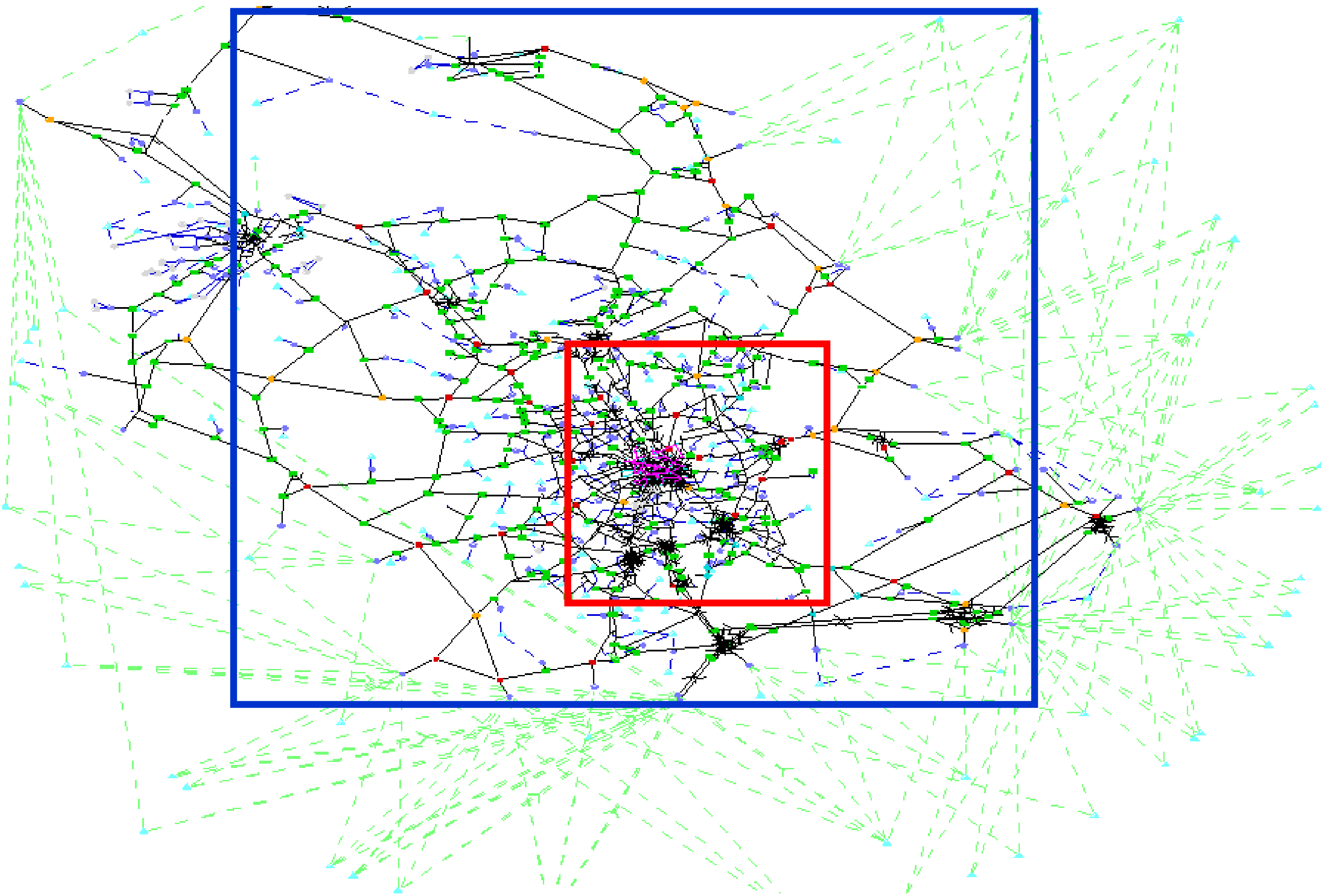


Figure 17 Bradford's SATURN Model Simulation Extent, red boxed ring road representing Bradford's Ring Road and blue boxed area representing Study Area, Source: Own Work (SATURN)

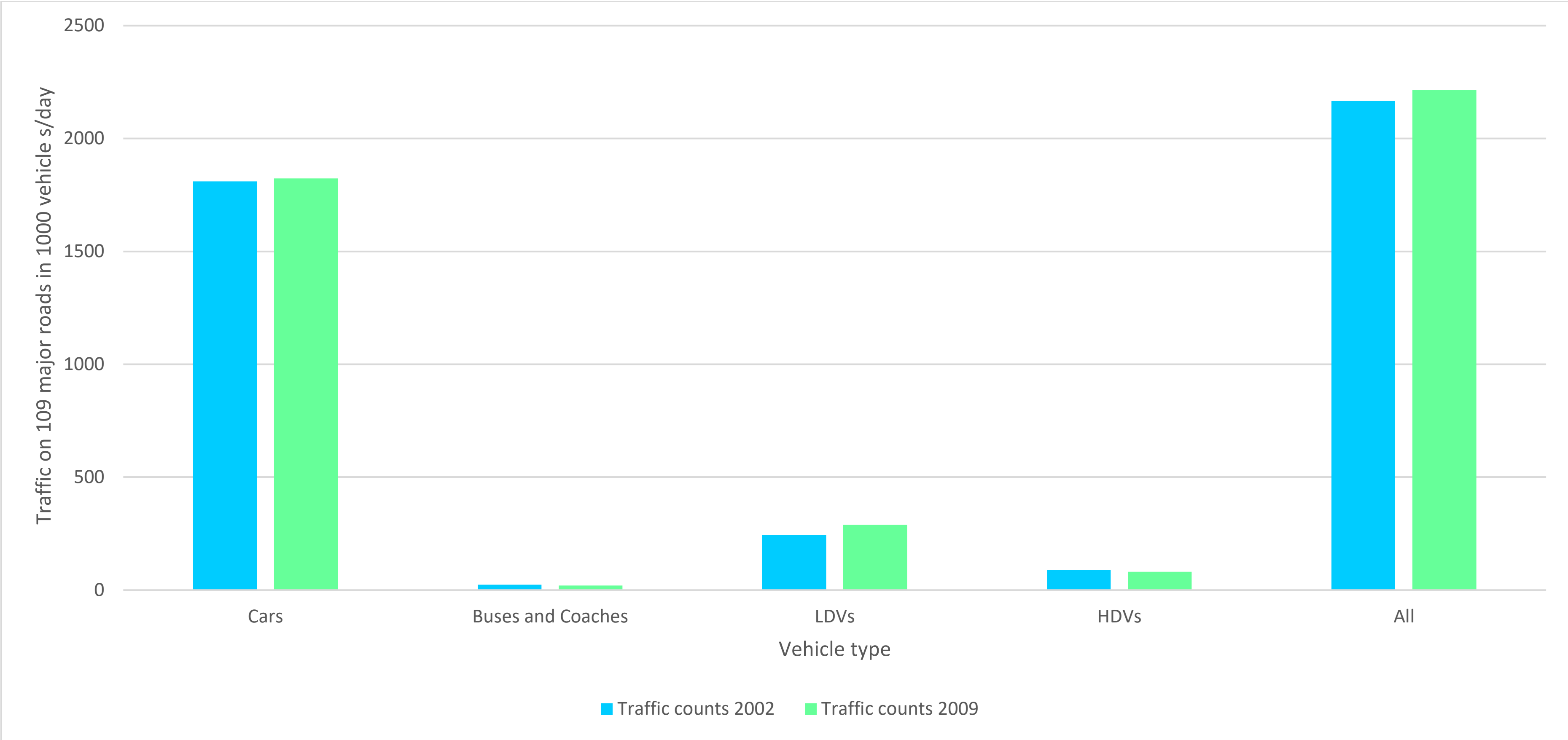


Figure 18 2002 and 2009 Cars, Buses and Coaches, LDVs and HDVs Traffic on Major Roads in Bradford (from 109 Traffic Counters), in 1000 Vehicles, Source: Own Work (Excel), Data Source: Department for Transport (2015b)

The updated SATURN model was used to extract the road's network physical characteristics and estimate the traffic flows and the average traffic speeds for three different time periods, on an average weekday:

- 1 x AM peak hour (08:00-09:00)
- Inter-peak hour (the average inter-peak hour between 10:00-16:00); and
- 1 x PM peak hour (17:00-18:00)

The author made the following decisions as to which results were extracted from the model's outputs. First, the traffic flows in SATURN were defined in two distinct ways:

1. The 'assigned' or 'demand' flow, which is the flow given by the assignment stage and corresponds to the total demand independent of when the flow arrives at the different consecutive junctions, and therefore double counts the queuing delays downstream of the actual queue.
2. The 'actual' or 'simulated' flow which corresponds to the actual flow during the time simulated considering the different flow arrivals at the different consecutive junctions, and therefore different hourly demand at all junctions.

A decision was made to extract the 'Actual flow (PCU/h)' reported in passenger cars unit per hour (PCU/h) rather than the 'Demand flow (PCU/h)' from the SATURN outputs. The actual flow is a more realistic representation of the flow arriving and departing from junctions in each simulated hour, which defines delays more realistically at over-capacity junctions allowing for long delays where queues form but also avoiding the problem of double counting traffic flows at subsequent junctions, which receive queued traffic gradually (SATURN Manual, 2015).

Second, the link speed that was extracted was the 'Net speed (+ Qs)' measured in kilometres per hour (km/h). This was considered the most relevant as it represented the speed based on total simulation link travel time including delay/queuing times.

Third, the parameter 'Distance (meters)' was extracted as the link's length in meters.

Fourth, the X (Easting) and Y (Northing) coordinates were extracted for all nodes connecting the network links (turning movements and zone connecters were excluded). Four columns were created containing the X coordinate of the A node, the Y coordinate of the A node, followed by the X and Y coordinates for the B node. The A nodes represented the start point of a link, while the B node represented the end of a link, which could also be the start point of another link(s). The X and Y coordinates were initially included in the model input files as free format restricted to 5 digits (i.e.

55555 records). Therefore, as the real X and Y coordinates are 6 digits, a lead number ('4') was added to all coordinates extracted from the model and this enabled mapping them in Bradford on a British National Grid system. The SATURN nodes were mapped over an Open Street Map in ArcMap, version 10.4. The Open Street Map was used as a reference layer to check for the node locations' accuracy. The A and B nodes were connected to each other by straight lines to represent the road links between them, following the model developers' practice (i.e. representing road links by straight lines). As will be shown in more detail later (Section 3.4.4), when mapped in ArcMap, the nodes were clearly not accurately geo-located and the SATURN road links were not accurately overlaying the roads in the reference Open Street layer.

To attempt to improve the sensibility of the nodes locations by linking them to specific roads in Bradford, the SATURN road links' X and Y coordinates were automatically manipulated in Spatialite, version 4.3.0, using a spatial function (GEOS v. 3.5.0) to snap the SATURN nodes onto their nearest roads, as defined by four hierarchal user-specific conditions. The code used for the snapping was written in Python by Antonia Valentin, GIS coordinator at the at the Barcelona Institute for Global Health, at the request of and in collaboration with the author. The final code used is available upon request. Snapping enables moving a point (the SATURN node in this case) from its current location to a new location, which coincides with another feature, as specified by the user (the underlying roads in this case) (ESRI, 2016). As such, nodes which were not overlaying a road, as they should be, were snapped onto their nearest road, as defined using two underlying Ordinance Survey Open Roads Maps (Figure 19), and following the user-specific conditions below:

1. The following input files were read into Spatialite version 4.3.0: the original X and Y coordinates of all the SATURN nodes, an underlying major roads map in Bradford, an underlying all roads maps in Bradford (Figure 19)
2. The original A and B nodes were connected by a straight line representing the road links and the length of these road links were calculated
3. ***Condition #1*** was applied: A and B nodes within 5 m of any road, as identified from the all roads Open Roads layer, were snapped onto the nearest road
   Nodes A – a total of 1548 have been snapped onto their nearest road ≤ 5 m
   Nodes B – a total of 1541 have been snapped onto their nearest road ≤ 5 m
4. ***Condition #2*** was applied: The remaining A and B nodes within 200 m of a major road, as identified from the major roads Open Roads layer, were snapped onto the nearest major road

Nodes A – a total of 1940 have been snapped onto their nearest major road ≤ 200 m

Nodes B – a total of 1943 have been snapped onto their nearest major road ≤ 200 m

5. ***Condition #3*** was applied: The remaining A and B nodes were snapped onto their nearest road within a 1 km buffer, as identified from the all roads Open Roads layer

   Nodes A – a total of 1012 have been snapped onto their nearest road (average distance of 42 m)

   Nodes B – a total of 1016 have been snapped onto their nearest road (average distance of 42 m)
6. ***Condition #4*** was applied: the new length of the road link between all the nodes that have been snapped had to remain within ±20% of the old length of the road link (see second point above) between the original (unsnapped) nodes. In the cases were the new length fell outside the ±20% range, the snapping was undone, and the nodes retained their original locations
7. Finally, 1161 A *and* B nodes retained their locations, i.e. the road links length remained the same as the original network. All other new road links were within ±20% of the old road link length
8. A new list of geo-locations for the snapped nodes was produced and visually examined for its sensibility

This geo-processing was assumed to improve the accuracy of the links start and end locations, and therefore the accuracy of the road link locations. This was visible by manual oversight as many of the nodes and links were in more reasonable positions compared to the original SATURN node locations. However, as the nodes and links' real locations remained imperfect and the degree of the improvement gained remained unknown/unquantified, both the geo-processed and unprocessed (original) node locations will be inputted in the dispersion models (Chapter 5), to test the effects of this geo-processing on air quality estimates and their validation.

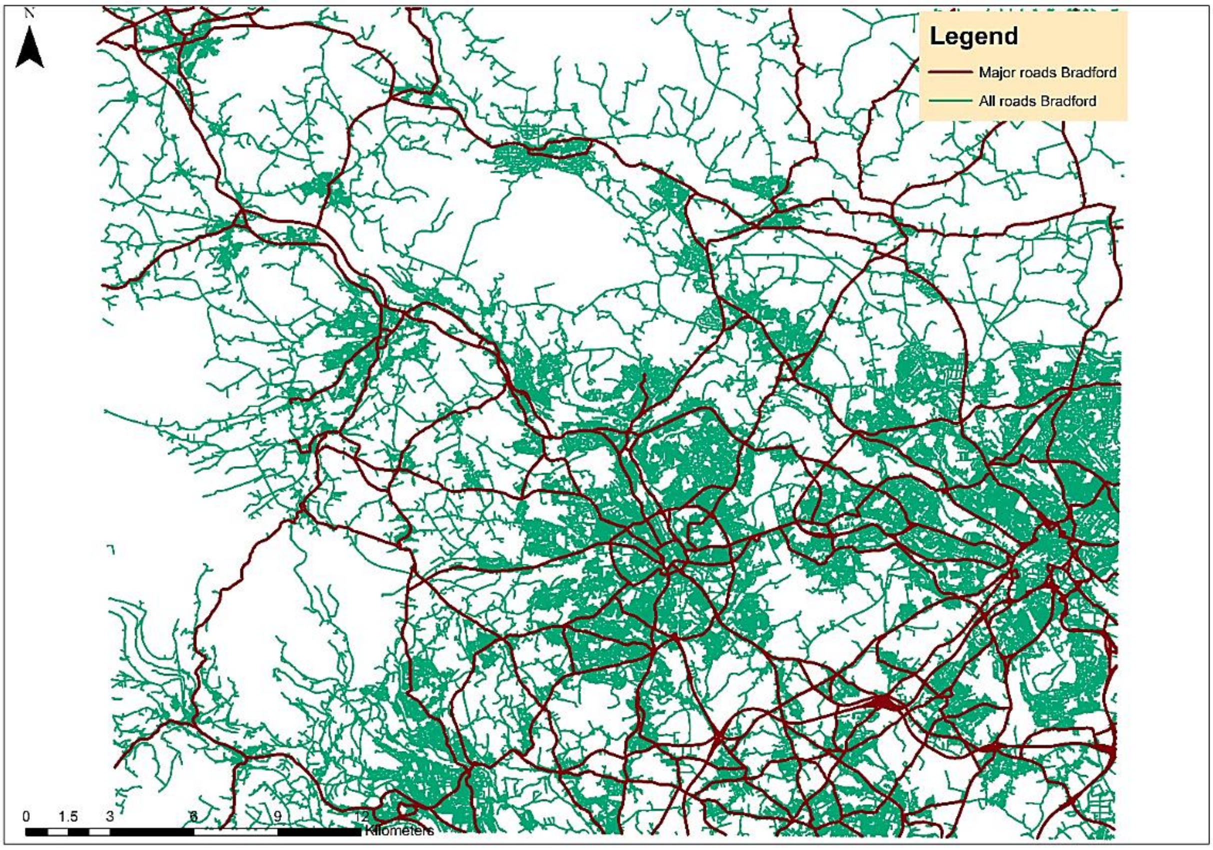


Figure 19 Major and All Roads Networks Used in Snapping Commands, Source: Own Work (ArcMap 10.4), Data Source: (Ordinance Survey Open Data 2016)

Finally, all modelled traffic flows in PCU/h were converted to vehicles/h using established proportions that were used in the original SATURN model set-up. The current SATURN model used the following PCU factors to represent the different vehicle classes/types (Moore, 2016):

- Cars and vans = 1.0 PCU;
- LDVs (<7.5t) = 1.5 PCU; and
- HDVs (>7.5t) and Buses/Coaches = 2.0 PCU.

Using these factors and the link's simulated flow in PCU/h, the traffic flow in vehicles/h can be calculated for each link using the following equation:

$$\text{Traffic flow}\left(\frac{\text{vehicles}}{\text{hour}}\right) = \frac{\text{Traffic flow}\left(\frac{\text{PCU}}{\text{hour}}\right)}{(\%\ \text{vehicle class } 1 * \text{PCU factor}) + (\%\ \text{vehicle class } 2 * \text{PCU factor}) + \cdots + (\%\ \text{vehicle class } N * \text{PCU factor})} \ldots \text{Equation 3.2}$$

.

Subsequently, the resulting traffic flows in vehicles/h were split into the different vehicle classes of the fleet by applying vehicle fleet composition proportions given in the National Atmospheric Emissions Inventory (NAEI) spreadsheets (National Atmospheric Emissions Inventory and Ricardo Energy and Environment, 2014). The NAEI spreadsheets are freely available from the Department for Environment Food & Rural Affairs website at: http://naei.defra.gov.uk/data/ef-transport and give vehicle proportions by vehicle class (e.g. passenger car, LDVs, HDVs, buses, coaches and motorcycles), EURO emission standard (pre-EURO to EURO 5/V), catalyst status (for petrol vehicles), weight class, and exhaust after-treatment technology where applicable.

3.4. Results

3.4.1. Traffic Flows and Vehicle Classes Fleet Split

The traffic flow at each road link was extracted for the three different simulated time periods: AM peak hour, inter-peak hour and PM peak hour. The traffic flow summary statistics are shown in Table 7. Road links were included in this analysis whilst turning movements and zone connecters in the model were excluded.

Table 7 Links Flows (PCU/h) Summary Statistics (N=4500 simulated links)

Statistic	AM peak	Inter-peak	PM peak
Minimum	0.00	0.00	0.00
1st quartile	51.19	47.66	60.94
Median	229.70	175.31	233.40
Mean	414.95	340.57	436.85
3rd quartile	617.73	505.61	655.26
Maximum	6017.25	5410.97	5925.03

The traffic flows simulated in SATURN in the AM peak hour, as an example, are shown in Figure 20 and Figure 21. As shown in these figures, the traffic flows were highest over the long motorway sections; the M62 and the M606 leading in and out of Bradford. There were also relatively high traffic flows on the A650 and A629 leading to Bingley and Keighley (North-West), and high flows within the Bradford Ring Road especially on Wakefield Road continuing the A658 (comparison made against underlying base maps, removed for better visuals).

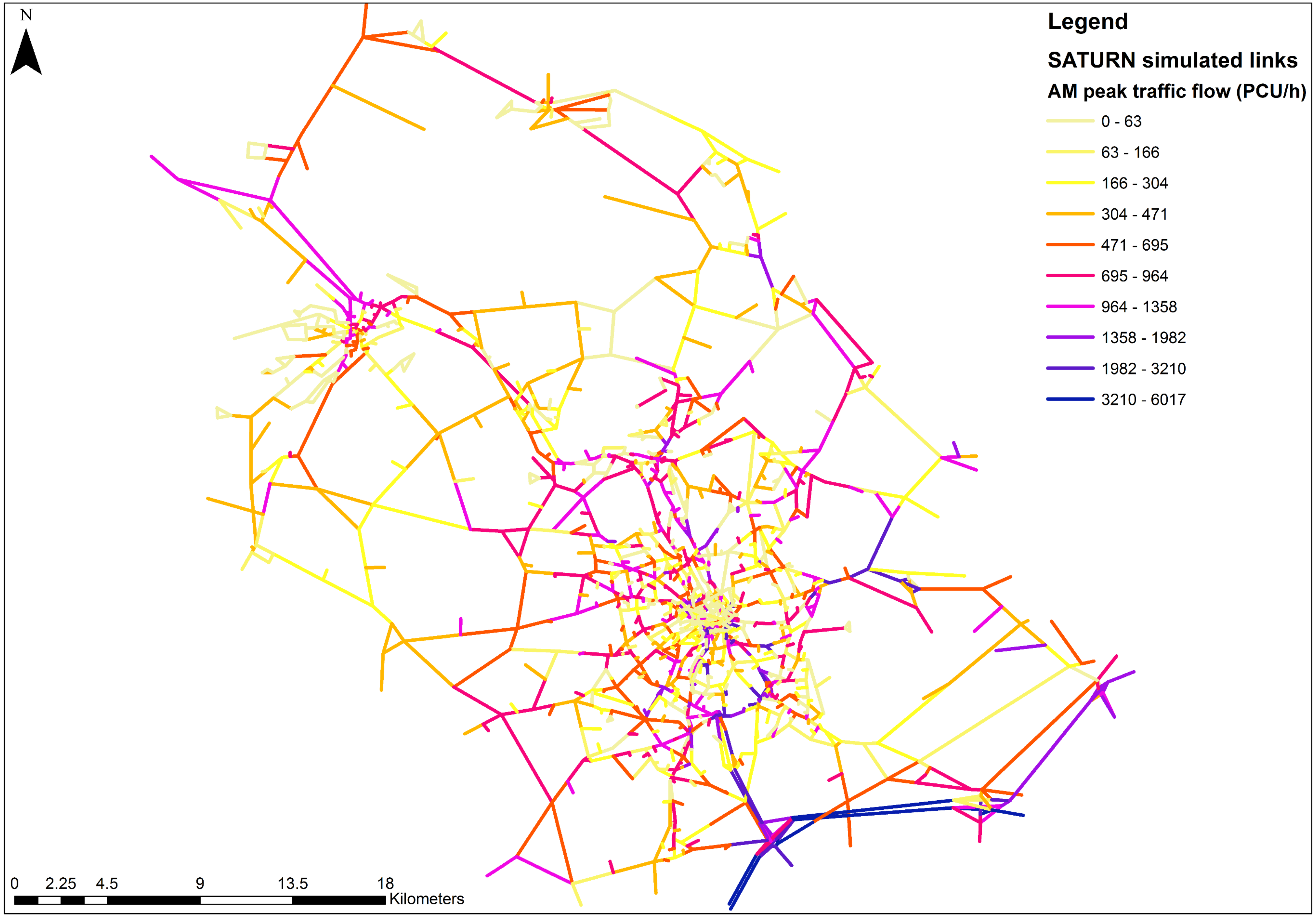


Figure 20 Bradford's SATURN Model Simulated Actual Flows (PCU/h) in AM Peak Hour, Source: Own Work (ArcMap 10.4)

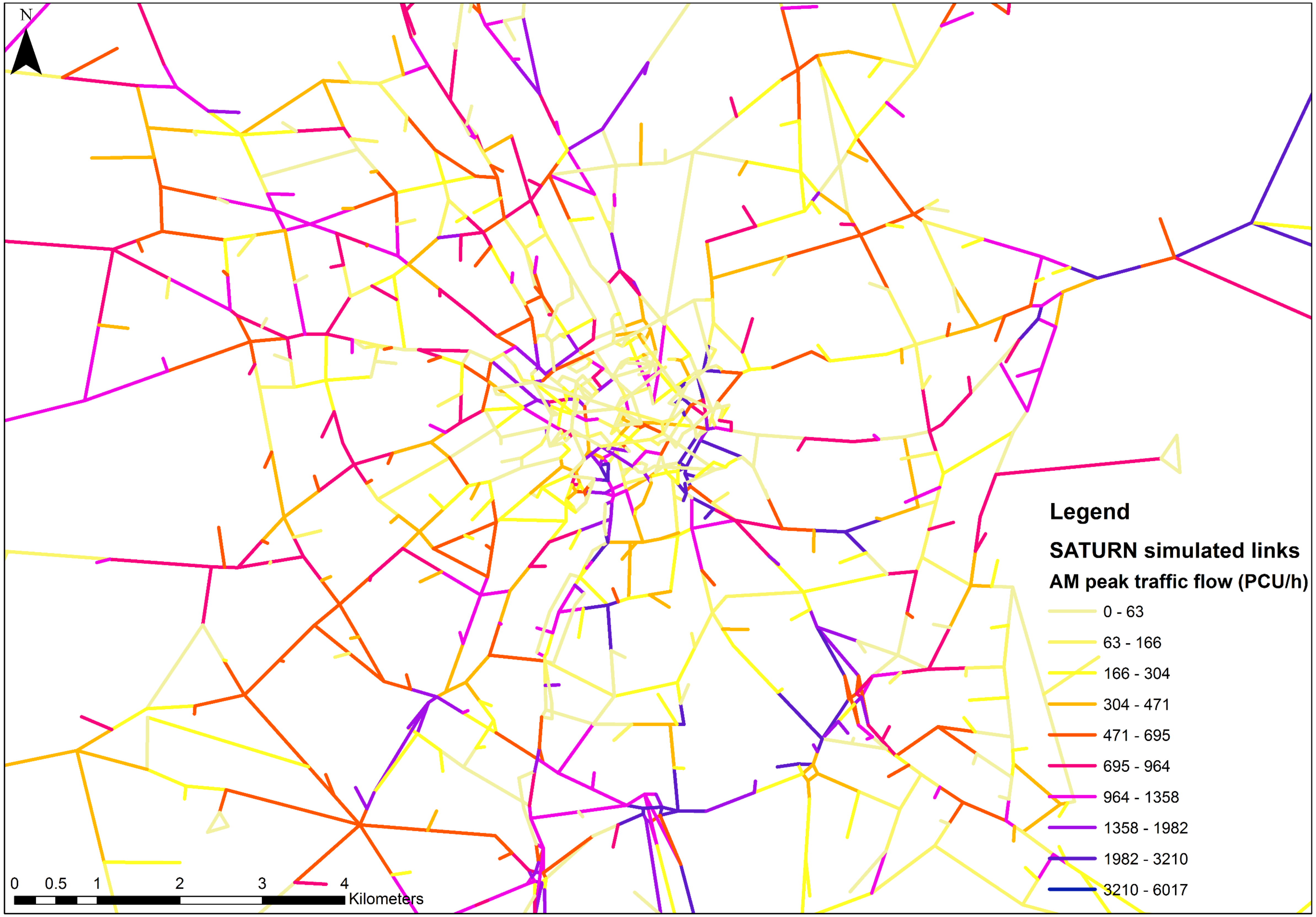


Figure 21 Bradford's SATURN Model Simulated Actual Flows (PCU/h) in AM Peak Hour Zoomed at City Centre, Source: Own Work (ArcMap 10.4)

The SATURN link traffic flows in PCU/h at each simulated time (AM peak hour, inter-peak hour, and PM peak hour) were extracted into an excel spreadsheet and these were converted into vehicles/h using Equation 3.2. The proportions of vehicle kilometre split by vehicle class/type for year 2009 in Urban England were extracted from The NAEI spreadsheets. The basic fleet percentages used for the fleet mix split are shown in Figure 22. The converted traffic flows in vehicles/h and the NAEI vehicle class percentages given in Figure 22 were used to proportion the vehicle flows into its different vehicle classes/types. Motorcycles were excluded from the current analysis as no emission factors could be established for them using the emission modelling methodology of this study (Chapter 4), and as their percentages are low (1.51%) and are even likely to be lower in Bradford than nationally reported figures.

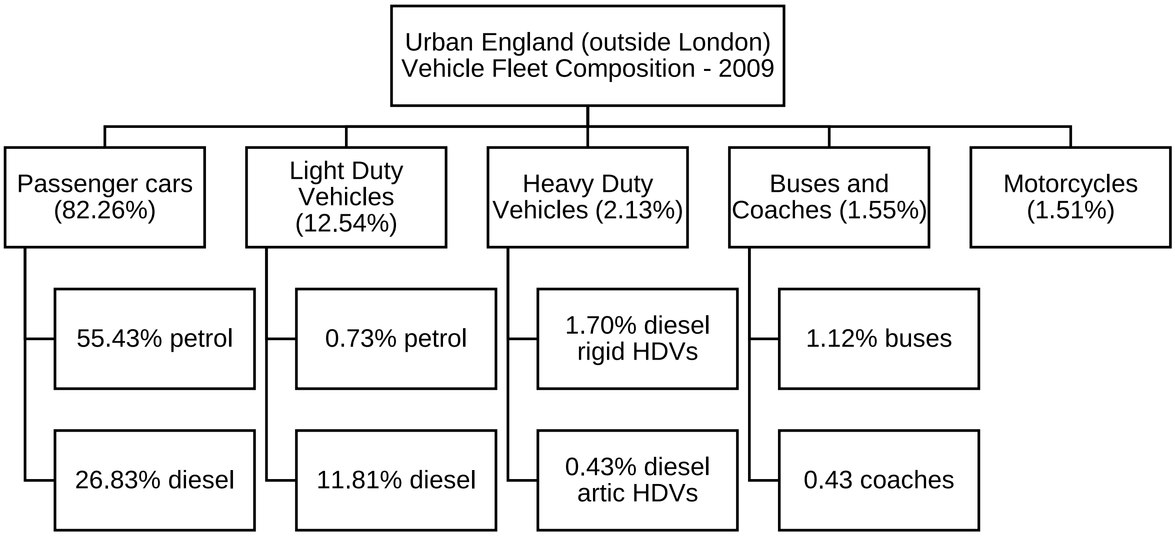


Figure 22 Proportion of Vehicle Kilometres by Vehicle Type in Urban England in 2009, Source: Own Work (Word), Data Source: National Atmospheric Emissions Inventory and Ricardo Energy and Environment (2014)

The resulting flows of each vehicle class in vehicles/h were further split into EURO emission standards, catalyst status (in the case of petrol passenger cars), weight categories (in the case of LDVs, HDVs, buses and coaches), and exhaust after-treatment technology including Exhaust Gas Recirculation (EGR) (Zheng et al., 2004) or Selective Catalytic Reduction (SCR) (Blakeman et al., 2007) (in the case of EURO V diesel HDVs). These proportions, as extracted from the NAEI spreadsheets, are shown in Table 8 and Table 9, and represent year 2009 in Urban England (National Atmospheric Emissions Inventory and Ricardo Energy and Environment, 2014). All road types were assumed to be Urban. When the catalyst of a petrol vehicle failed, the NAEI spreadsheet recommends using pre-EURO emission factors for that vehicle, and this recommendation was followed. The proportion of EURO V HDVs equipped with a SCR and EGR were 0.75 and 0.25, respectively (National Atmospheric Emissions Inventory and Ricardo Energy and Environment, 2014). In the public service vehicle category, the proportion of buses and coaches were 0.72 and 0.28, respectively (National Atmospheric Emissions Inventory and Ricardo Energy and Environment, 2014).

Table 8 UK Traffic Fleet Composition – Proportion of Vehicle Kilometres by EURO Emission Standard and Catalyst Status, in Urban England in 2009, Source: National Atmospheric Emissions Inventory and Ricardo Energy and Environment (2014)

EURO standard	Petrol cars	Diesel cars	Petrol LDVs	Diesel LDVs	Rigid HDVs	Artic HDVs	Buses and Coaches
Pre-EURO	0.01	0.00	0.06	0.00	0.00	0.00	0.01
EURO 1	0.04 catalyst OK	0.02	0.06 catalyst OK	0.01	0.01	0.00	0.02
	0.01 catalyst FAILS		0.01 catalyst FAILS				
EURO 2	0.15 catalyst OK	0.07	0.30 catalyst OK	0.10	0.13	0.04	0.21
	0.03 catalyst FAILS		0.06 catalyst FAILS				
EURO 3	0.42 catalyst OK	0.37	0.25 catalyst OK	0.33	0.47	0.42	0.45
	0.01 catalyst FAILS		0.04 catalyst FAILS				
EURO 4	0.34 catalyst OK	0.53	0.19 catalyst OK	0.56	0.26	0.35	0.21
	0.00 catalyst FAILS		0.01 catalyst FAILS				
EURO 5	None available	None available	None available	None available	0.13	0.19	0.11

Table 9 Vehicle Class Specific Weight Fraction of Fleet, Source: National Atmospheric Emissions Inventory and Ricardo Energy and Environment (2014)

Weight class	Petrol LDVs	Diesel LDVs	Rigid HDVs	Weight class	Artic HDVs	Buses and Coaches
N1 (I)/ Class I	0.06	0.06	NA	14-20 tonnes	0.027	NA
N1 (II)/ Class II	0.26	0.26	NA	20-28 tonnes	0.036	NA
N1 (III)/ Class III	0.68	0.68	NA	28-34 tonnes	0.027	NA
3.5-7.5 tonnes	NA	NA	0.348	34-40 tonnes	0.189	NA
7.5-12 tonnes	NA	NA	0.063	40-50 tonnes	0.720	NA
12-14 tonnes	NA	NA	0.025	Urban Buses Midi <=15 tonnes (Single-Decker)	NA	0.314
14-20 tonnes	NA	NA	0.118	Urban Buses Standard 15 – 18 tonnes (Double-Decker)	NA	0.686
20-26 tonnes	NA	NA	0.161	Urban Buses Articulated > 18 tonnes (Bendy Buses)	NA	0.00
26-28 tonnes	NA	NA	0.082	Coaches Standard <=18 tonnes (Small)	NA	0.50
28-32 tonnes	NA	NA	0.163	Coaches Articulated >18 tonnes (Large)	NA	0.50
>32 tonnes	NA	NA	0.041			

3.4.2. Traffic Speeds

The traffic speed at each road link was extracted for the three different simulated time periods: AM peak hour, inter-peak hour and PM peak hour. The average link speeds simulated in SATURN in the AM peak hour, as an example, are shown in Figure 23 and Figure 24. As shown in these figure, the traffic is fastest on the motorway sections and larger roads outside the city while speeds are reduced around the city's Ring Road and within it.

The traffic speed summary statistics are shown in Table 10. Road links were included in this analysis whilst turning movements and zone connecters were excluded. The average speed across the three periods was around 33 km/h and was lowest in the PM peak than the AM peak and was slightly higher in the inter-peak period. The maximum speed simulated was 80 km/h across all three periods. The frequency of the average link speeds in the three periods simulated in the study area is shown in Figure 25. Each histogram bin is equal to 5 km/h.

Over half of all links had an average speed less than or equal to 40 km/h, reflecting the urban nature of most links in this road network. A very low percentage of links (≈

1.6%) had average speeds exceeding 60 km/h, and as shown in Figure 23, these are most likely to be the roads outside the city including motorways.

Table 10 Links Speeds (km/h) Summary Statistics (4500 simulated links)

Statistic	AM peak	Inter-peak	PM peak
Minimum	0.04	0.04	0.05
1st quartile	26.22	27.48	25.45
Median	40.00	40.00	40.00
Mean	33.51	33.97	33.22
3rd quartile	41.00	41.00	41.00
Maximum	80.00	80.00	80.00
% links with ≤ 10 km/h	11.04	9.89	11.67
% links with 0-40 km/h	55.44	55.02	55.71
% links with >40-60 km/h	40.58	43.31	42.73
% links with > 60 km/h	1.62	1.67	1.56

3.4.3. Link Lengths

The link lengths summary statistics are shown in Table 11 and Figure 26. Only road links were included in this analysis whilst turning movements and zone connecters were excluded. 38% of all links were ≤ 100 m in length and 50% were <172 m. The distribution of the link lengths across the road network is shown Figure 26. Each histogram bin is equal to 50 m.

Table 11 Link Lengths (meters) Summary Statistics (4500 simulated links)

Statistic	Link length (m)
Minimum	1.0
1st quartile	50.0
Median	172.0
Mean	302.1
3rd quartile	327.2
Maximum	6000.0

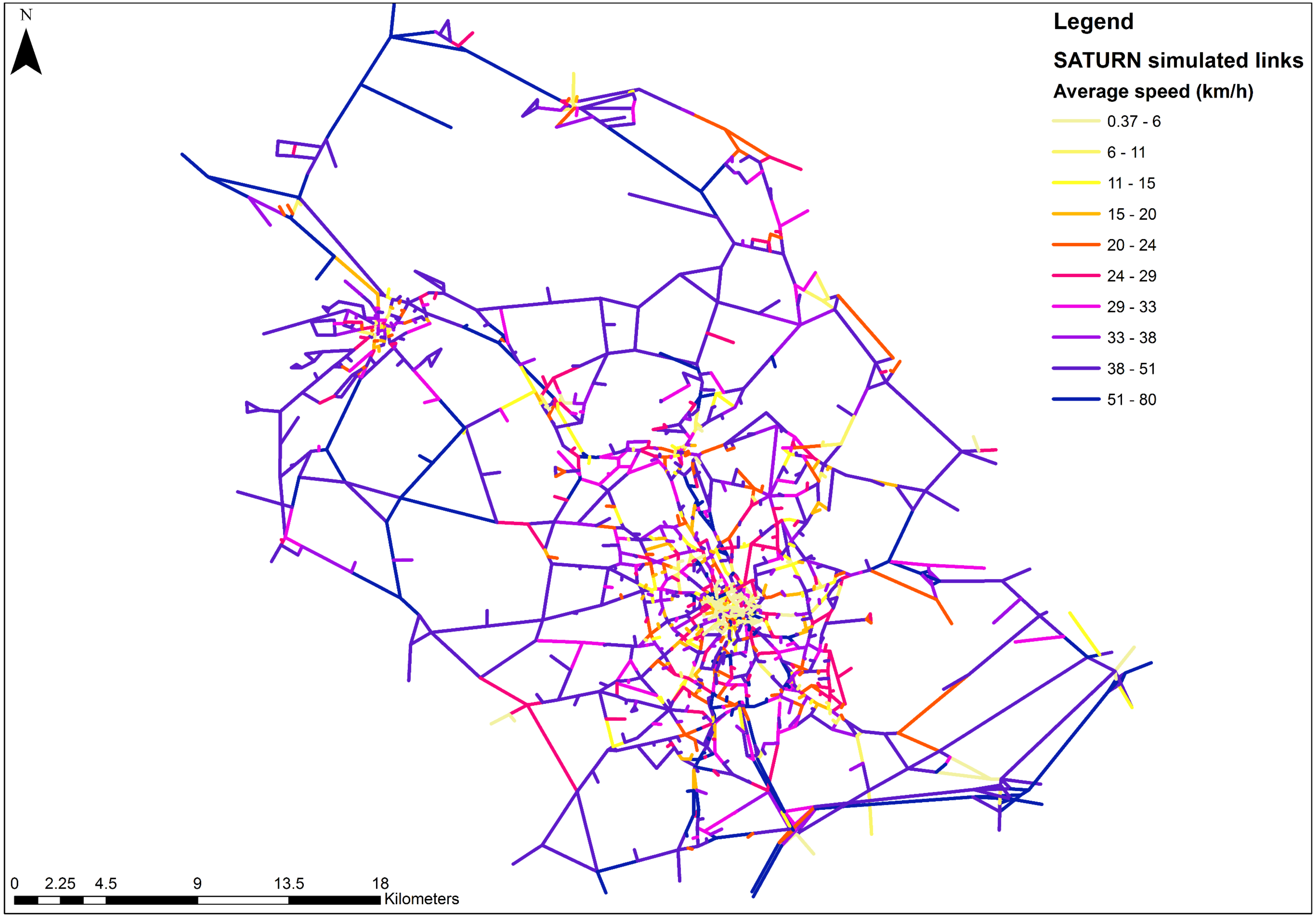


Figure 23 Bradford's SATURN Model Simulated Net Speed (km/h) in AM Peak Hour, Source: Own Work (ArcMap 10.4)

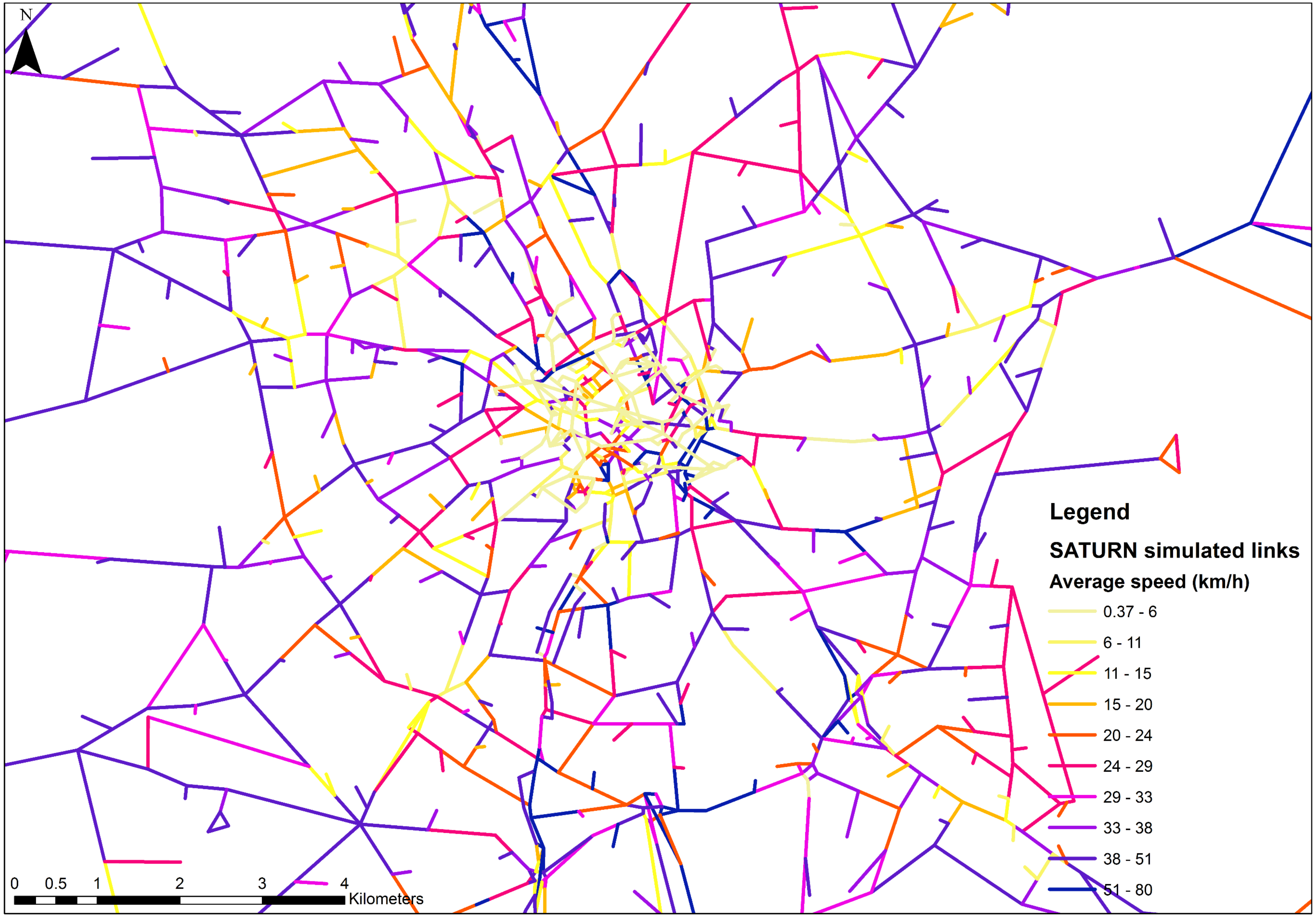


Figure 24 Bradford's SATURN Model Simulated Net Speed (km/h) in AM Peak Hour Zoomed at City Centre, Source: Own Work (ArcMap 10.4)

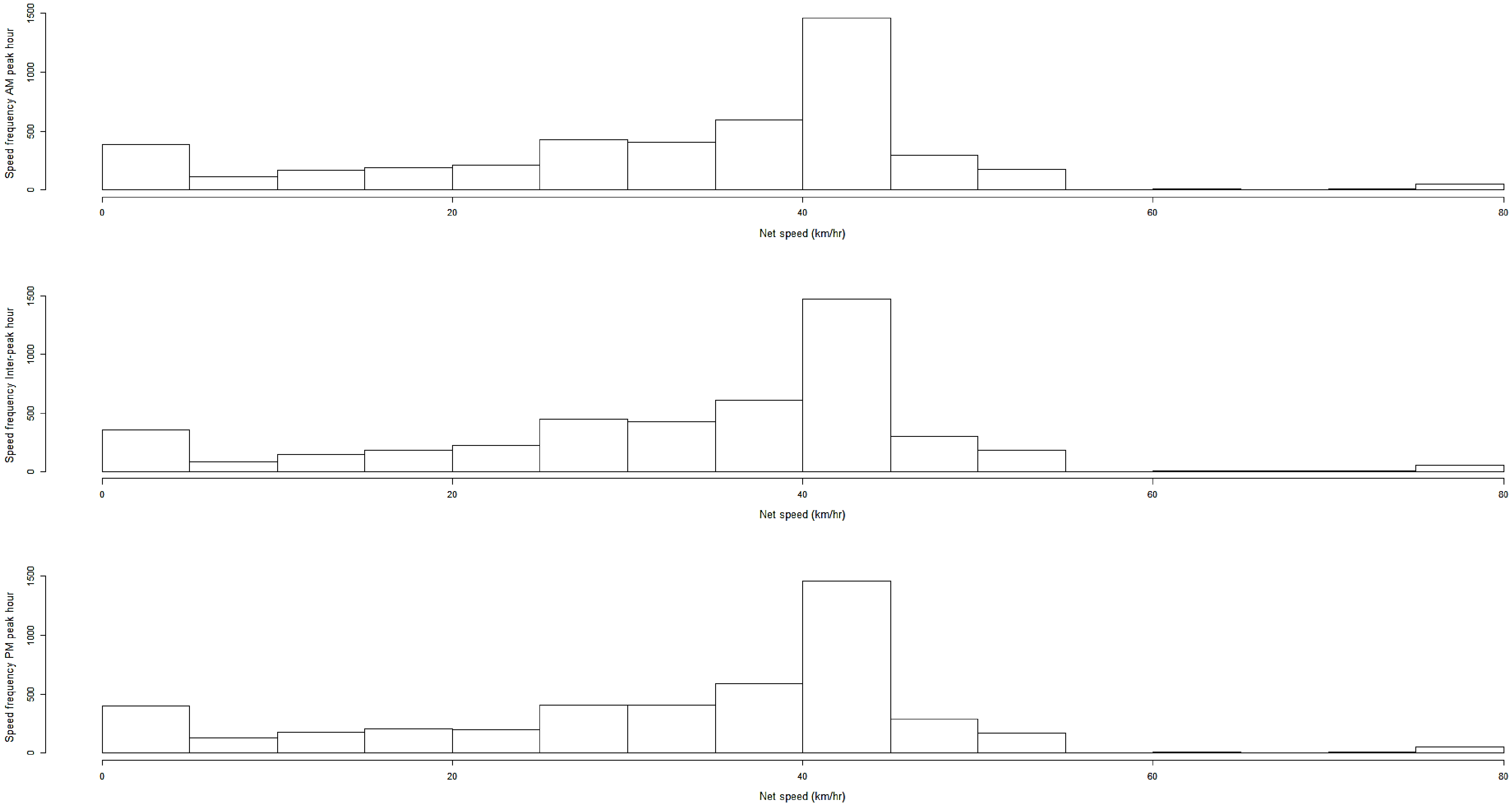


Figure 25 Histogram of Link Speeds from Bradford AM Peak Hour (top), Inter-peak Hour (middle), and PM Peak Hour (bottom) SATURN Model, Source: Own Work (R)

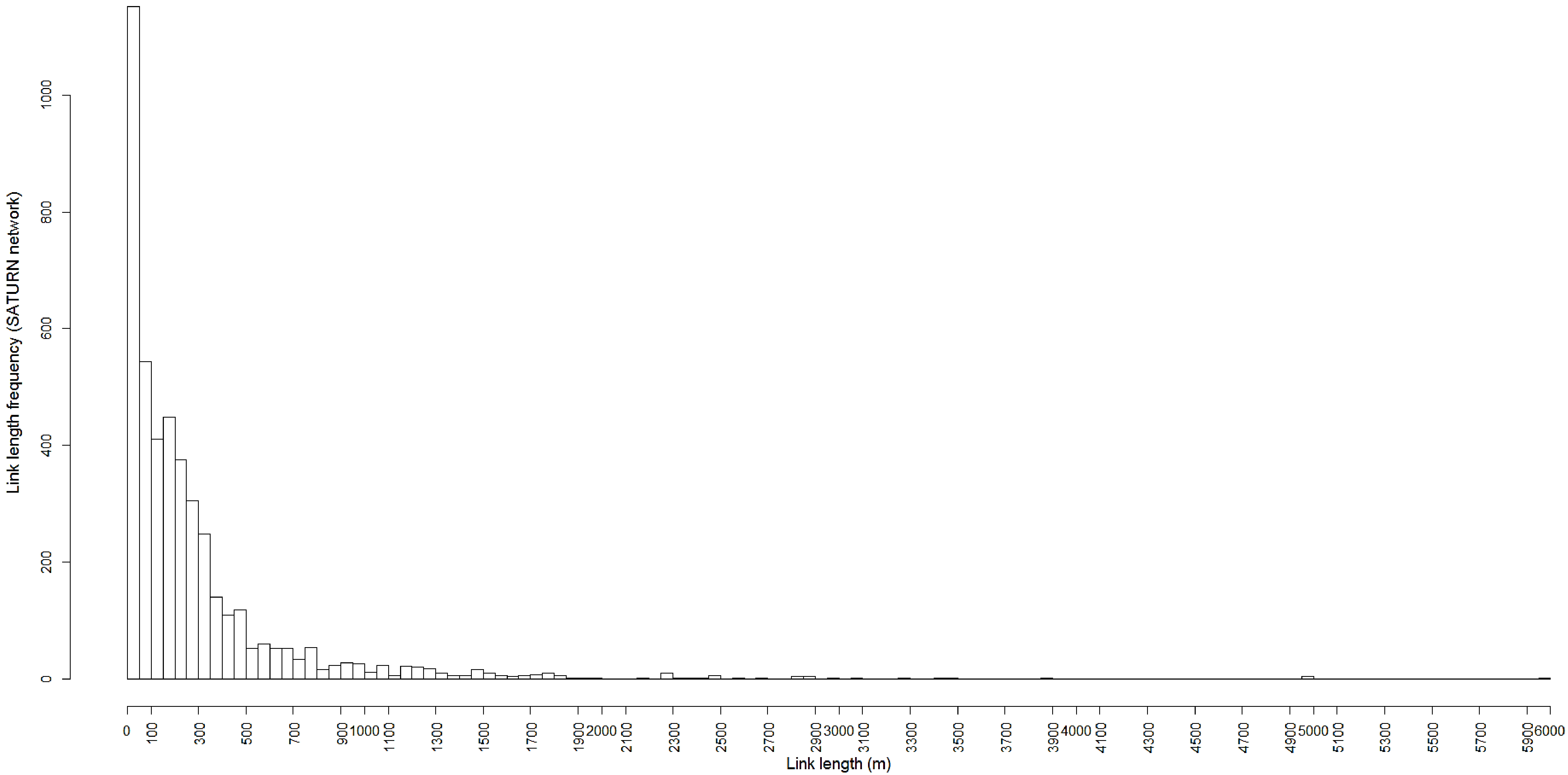


Figure 26 Histogram of Link Lengths in Bradford's SATURN Model, Source: Own Work (R)

3.4.4. Geographical Locations

The X and Y coordinates as originally inputted in the SATURN model were extracted for all nodes connecting the network links. Only road links were included in this analysis whilst turning movements and zone connecters were excluded. Plotting the SATURN nodes in ArcMap showed that there is a topographic correspondence between the nodes and major roads and junctions, as shown in Figure 27.

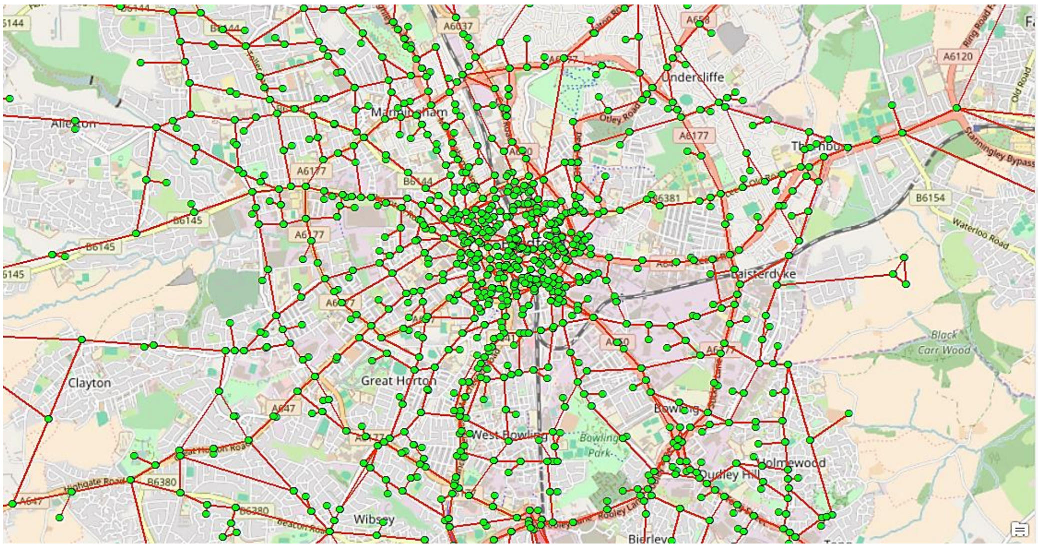


Figure 27 SATURN Nodes plotted in ArcMap (Green Circles) and connected by Straight Lines (Red) to represent the Road Links, Underlying Base Map is Open Street Map, Source: Own Work (ArcMap 10.4)

There were numerous places, however, where the SATURN nodes/links were offset topographically from the actual junction locations/roads. This was identified from manual oversight by comparing the plotted SATURN network to an underlying Open Street map. The SATURN nodes layer also illustrated that it seems to be common practice that minor roads e.g. cul-de sacs feeding into a more major road were often agglomerated into a single link. A closer investigation of the node locations also revealed that some of the nodes were apparently not correctly geo-referenced, as some nodes were not placed on roads or did not follow the expected/reasonable link path. Overall, the SATURN network was a considerable simplification of the road network and the nodes were not accurately geo-referenced.

Figure 28 is a snapshot of part of the Bradford SATURN network (south-west of the ring road) which illustrates the above points – the remainder of the network looks similar. To attempt to overcome some of the inaccuracies in the road links' geo-locations, the node locations were reprocessed as described in Section 3.3.4. Manual vector editing, manually moving nodes into their expected correct locations, was excluded as an option for geo-processing in this research study as it was considered highly time consuming and error prone due to the complexity of the network. GIS experts were consulted regarding how to best geo-process the network and two independent opinions advised that manual vector editing should be ruled out as the road network is large and complex and there is a lack of understanding of how it was initially built and geo-coded in the original transport model (e.g. whether it has used local rather than national coordinates, whether lower-level streets were agglomerated into single links and under which circumstances, differentiating between the two direction of traffic and whether the model has used the shortest path) (Namdeo, 2016, Valentin, 2016). Figure 29 illustrates the differences between the locations of the original (red) and snapped (green) nodes. It was assumed that the geographical locations of the snapped nodes were more accurate, but both the processed and the unprocessed road network (original) were further investigated in subsequent work to explore the effect of the snapping on the final air quality estimates and their validation.

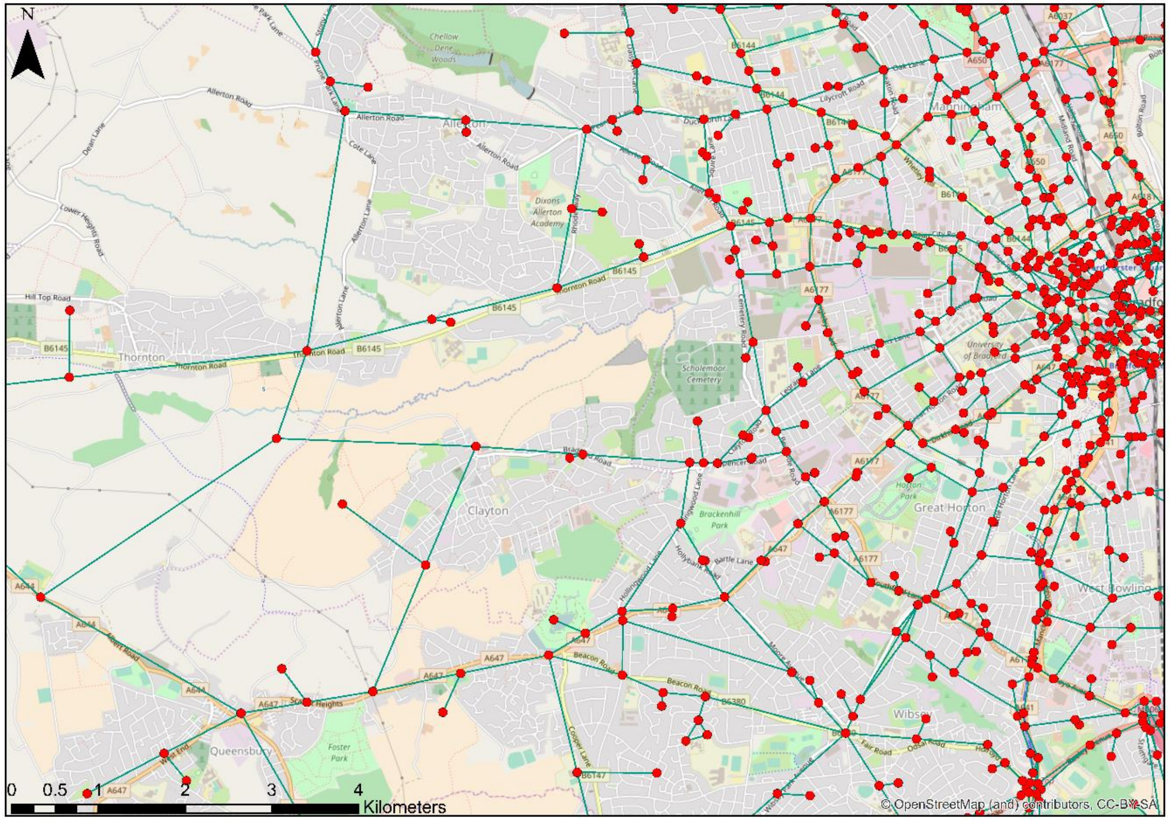


Figure 28 Snapshot of the Original SATURN Network, Red Circles Represent Original Node Locations Connected by Straight Lines Representing Road Links, Source: Own Work (ArcMap 10.4)

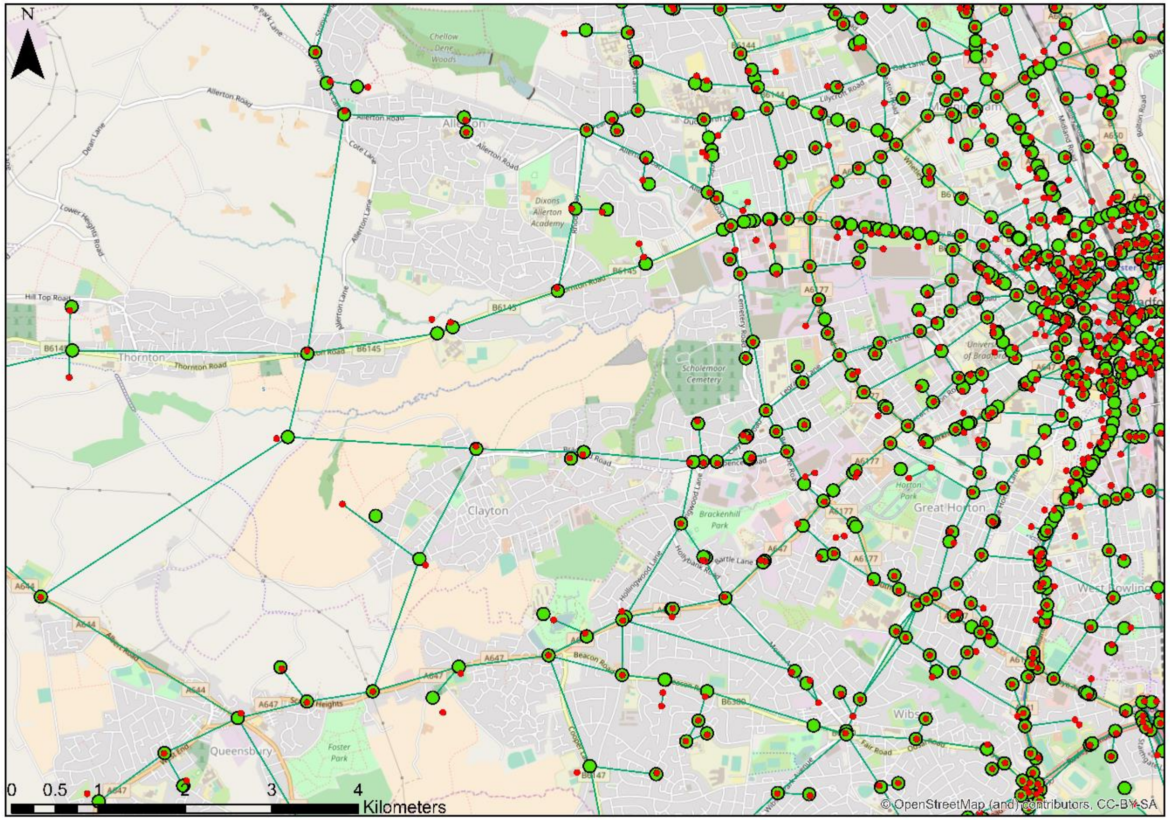


Figure 29 Snapshot of the Original SATURN Node Locations (in Red) versus Snapped Nodes Locations (in Green) Connected by Straight Lines Representing Road Links, Source: Own Work (ArcMap 10.4)

3.4.5. Traffic Flows Validation and Diurnal Scaling

As there was relatively little detail on the techniques used in the validation of the Bardford's SATURN model and as the calibration links used so that the model can attempt to adjust the flows in the matrix to the observed flows were the same links used for validation (i.e. there was no independent validation data set) (Steer Davies Gleave, 2009), an independent validation exercise was undertaken.

The results of this validation are illustrated in Figure 30 and are numerically presented in the supplementary data of Khreis et al. (2017b). The results showed that this model's validation, in contrast to the validation reported by the developers (Section 3.3.4.), does not achieve the 85% DMRB threshold, where 85% of cases should have individual flows with a GEH < 5.0 (Section 3.3.3.). Specifically:

- **AM Peak: 66% of cases had GEH < 5** (12/35 points or 34% had a GEH > 5)
- **Inter-peak: 77% of cases had GEH < 5** (8/35 points or 23% had a GEH > 5)
- **PM Peak: 65% of cases had GEH < 5** (13/35 points or 35% had a GEH > 5)

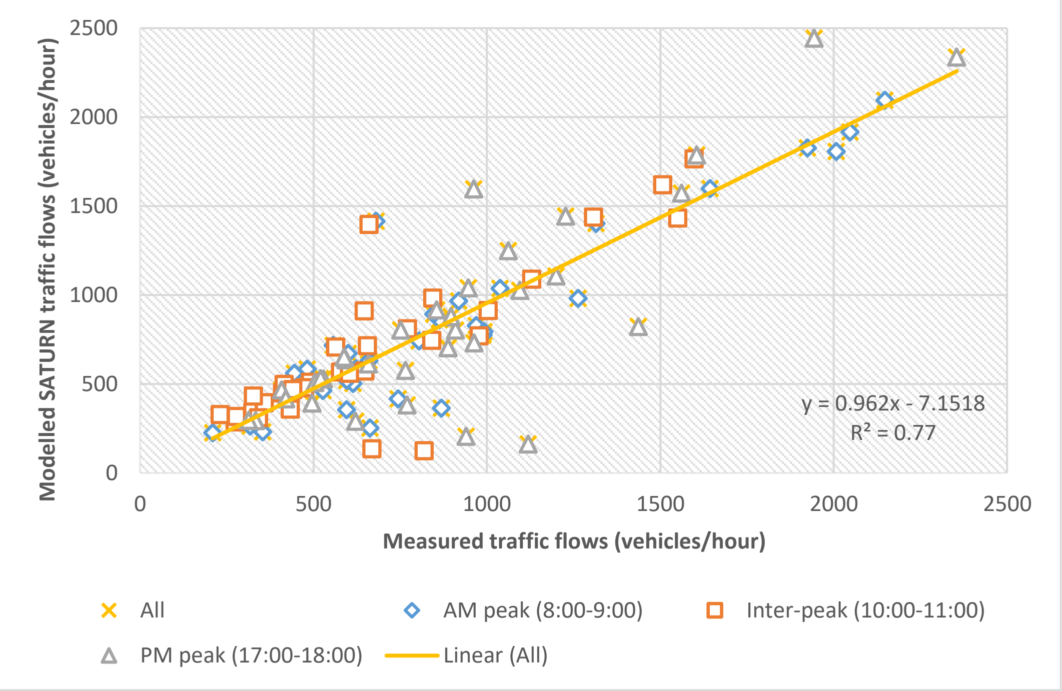


Figure 30 Measured Traffic Flows versus Modelled Traffic Flows (SATURN) in vehicles/h across all time periods (AM peak: green; Inter-peak: blue; PM peak: yellow) at 19 Traffic Counter Locations, representing 35 Directions of Travel, Source: Own Work (Excel)

The individual links comparison is shown in the supplementary data of Khreis et al. (2017b). This validation exercise, however, needs to be viewed as limited to a select number of links and a select ‘neutral’ week with full hour-by-hour traffic flow data, although this is standard practice. As shown inFigure 30, there was generally good agreement between measured and modelled traffic flows to support the use of this SATURN model. The 10 data points that are most deviating are where measured flows are > 500 and < 1200; and modelled flows <500 vehicles/h. The sources of these data points were double checked and found to be coming from 3 streets, which are generally smaller/ lower-level road than other major roads included in the validation, namely: B6381 Barkerend Road, A6181 Hamm Strasse and Cleckheaton Rd Oakenshaw. Overall, the SATURN model seems to be less valid for these smaller road links and tended to under estimate traffic levels.

To undertake the traffic scaling over the 24 hours of the average weekday, the procedure shown in Figure 31 was followed and is described next.

Hour-by-hour traffic flows were extracted from the 19 ATC (reporting on 35 directions of travel) at which the validation was undertaken (see above). The hourly traffic flows were averaged across all the counters to obtain one average traffic flow at each hour of the day (00:00 to 23:00). The result was a diurnal traffic flow profile in Bradford for year 2009, as shown in Figure 32. The diurnal traffic profile showed that the average traffic flows were highest at 07:00-09:00 AM, during morning rush hour, with another peak around 15:00-17:00 PM, which is likely to be representing the afternoon rush hour. The average traffic flows were lowest between 00:00-5:00 AM.

These hourly average traffic flows were used to scale the modelled traffic flows from SATURN (only simulated for the AM peak, inter-peak and PM peak hours) across the other missing hours of the day. To carry out the scaling, the observed/modelled ratios were calculated using the data shown in Figure 32, by dividing the average observed traffic flows (averaged across the 19 ATC) by the average SATURN traffic flows (averaged across the corresponding links), for the AM peak, the first inter-peak and PM peak hours. The observed/modelled ratios calculated were relatively consistent over the three modelled periods and were 1.08, 0.98, and 1.07 for the AM peak, inter-peak and PM peak hours, respectively (Table 12). These results suggest that the model is well predictive at the aggregate level, but less so at the link level where the variation between observed and modelled traffic flows becomes higher (Khreis et al., 2017b). No adjustment was attempted to match the modelled and the observed traffic flows, due to the very limited (in space and time) validation data set available.

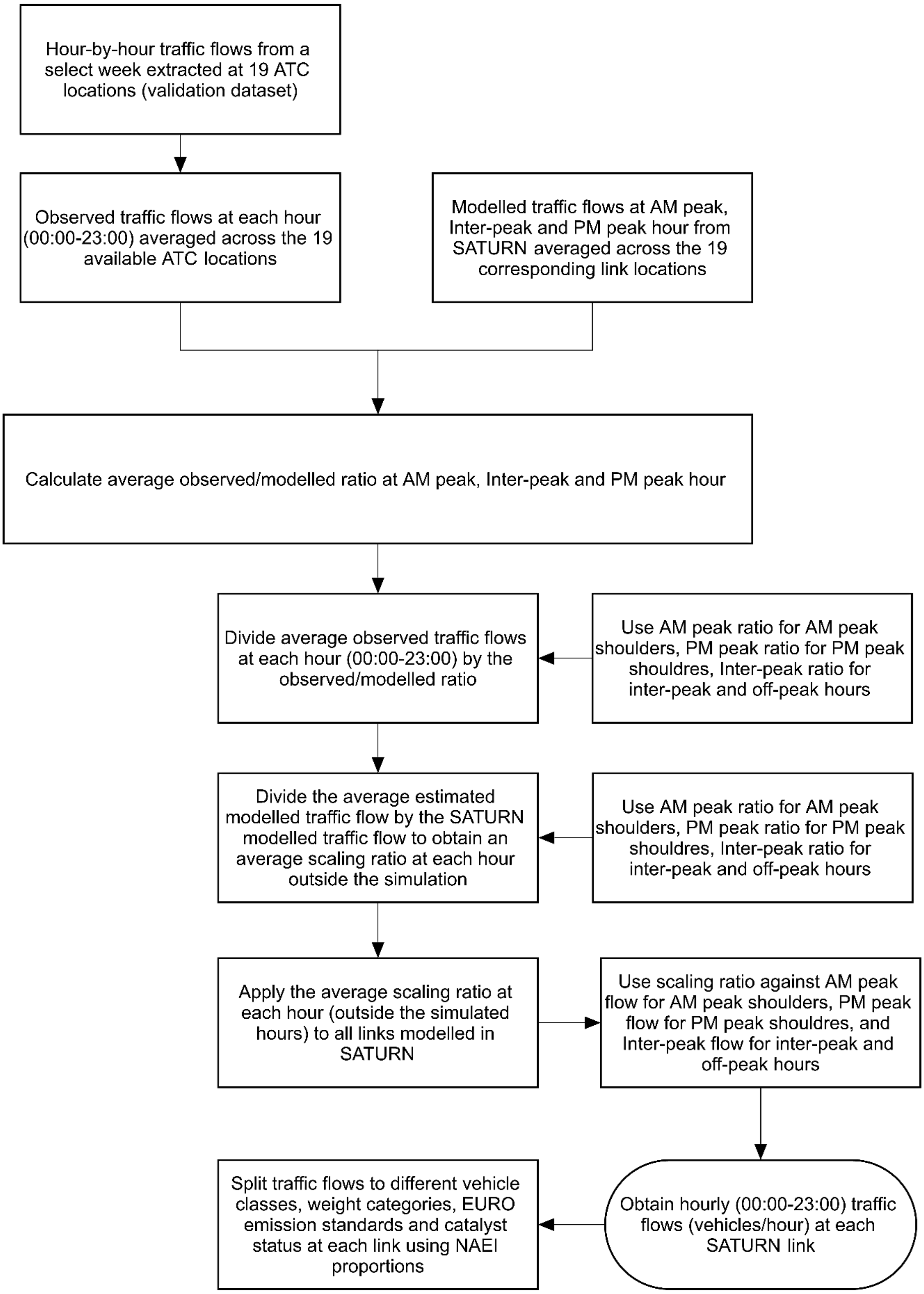


Figure 31 Traffic Flow Scaling Procedure, Source: Own Work (NCH Software)

Table 12 Average Traffic Flows Observed/Modelled Ratios (Weekdays)

Statistic	AM peak (08:00-09:00)	Inter-peak (10:00-11:00)	PM peak (17:00-18:00)
ATC flow average (19 points)	896.03	667	904.09
SATURN average (corresponding links)	830.94	682.03	841.94
Observed/modelled ratio (ATC average/SATURN average)	1.08	0.98	1.07

For all hours outside the model's simulation periods (00:00-08:00, 09:00-10:00, 11:00-12:00, 12:00-13:00, 13:00-14:00, 14:00-15:00, 15:00-16:00, 16:00-17:00, and 18:00-00:00), these ratios (Table 12) were used to scale the average observed traffic flows at the counter locations to an assumed/estimated modelled flow, as follows:

- AM peak shoulder 1 (07:00-08:00 AM) = Observed traffic flows at 07:00-08:00 / 1.08
- AM peak shoulder 2 (09:00-10:00 AM) = Observed traffic flows at 09:00-10:00 / 1.08
- Inter-peak hours (11:00 AM-15:00 PM) = Observed traffic flow at that hour / 0.98
- PM peak shoulder 1 (16:00-17:00 PM) = Observed traffic flows at 16:00-17:00 / 1.07
- PM peak shoulder 2 (18:00-19:00 PM) = Observed traffic flows at 18:00-19:00 / 1.07
- Off-peak hours (hours between 19:00 PM-7:00 AM) = Observed traffic flow at that hour / 0.98

The inter-peak period flows were altered (i.e. not assumed constant between 10:00-16:00) as the observed traffic flows in this period were varying in contrast to the SATURN model's assumption/estimates. This was done by choosing the first inter-peak hour (which was validated, see above) and using its observed/modelled ratio to factor the flows at other inter-peak hours. The resulting derived/estimated modelled average traffic flows are shown in Figure 33 for all hours outside the simulation period.

Next, this scaling needed to be undertaken at each of the 4500 modelled road links in SATURN. For this, the derived/estimated hourly modelled traffic flow (Figure 33) was divided by the modelled AM peak, inter-peak, and PM peak hour SATURN modelled traffic flow (which is the only available information for all 4500 links) to obtain an average factor to scale the traffic flows at each link for each hour outside the simulation. The rules given in the bullet points above were followed. At each link, this factor was multiplied by the AM peak, inter-peak, and PM peak hour SATURN modelled traffic flow at that link, to obtain a traffic flow for all hours outside the simulation, following the rules given in the bullet points above. Finally, for each hour, the traffic flows estimated were split into the fleet's vehicle classes/types as discussed in 3.5.1. The result was an hourly (00:00-23:00) traffic flow (vehicles/h) and a fleet mix matrix (split by vehicle type, EURO emission standard, catalyst status, weight category and exhaust after-treatment technology) for 4500 road links in Bradford, on an average weekday in year 2009. For weekend traffic flows, the hour-by-hour traffic flows on Saturday and Sunday were extracted at the 19 ATC and averaged across all counters. The traffic averages are shown in Figure 34 and show the different traffic patterns of the weekends. The ratio between these average hourly flows and the average AM SATURN traffic flow (from the validated links) was used to scale the individual links' traffic across all weekend hours. These ratios are shown in Table 13.

Table 13 Average Traffic Flows Observed/AM Modelled Ratios (Weekends)

Hour	ATC flow average (19 points)	SATURN AM average	ATC/SATURN AM
00:00	170.94	830.94	0.21
01:00	127.49	830.94	0.15
02:00	91.91	830.94	0.11
03:00	69.66	830.94	0.08
04:00	56.17	830.94	0.07
05:00	68.80	830.94	0.08
06:00	105.71	830.94	0.13
07:00	171.09	830.94	0.21
08:00	265.14	830.94	0.32
09:00	405.57	830.94	0.49
10:00	568.60	830.94	0.68
11:00	650.03	830.94	0.78
12:00	727.60	830.94	0.88
13:00	770.40	830.94	0.93
14:00	766.49	830.94	0.92
15:00	732.03	830.94	0.88
16:00	710.40	830.94	0.85
17:00	651.49	830.94	0.78
18:00	553.17	830.94	0.67
19:00	466.49	830.94	0.56
20:00	358.11	830.94	0.43
21:00	307.63	830.94	0.37
22:00	245.97	830.94	0.30
23:00	192.43	830.94	0.23

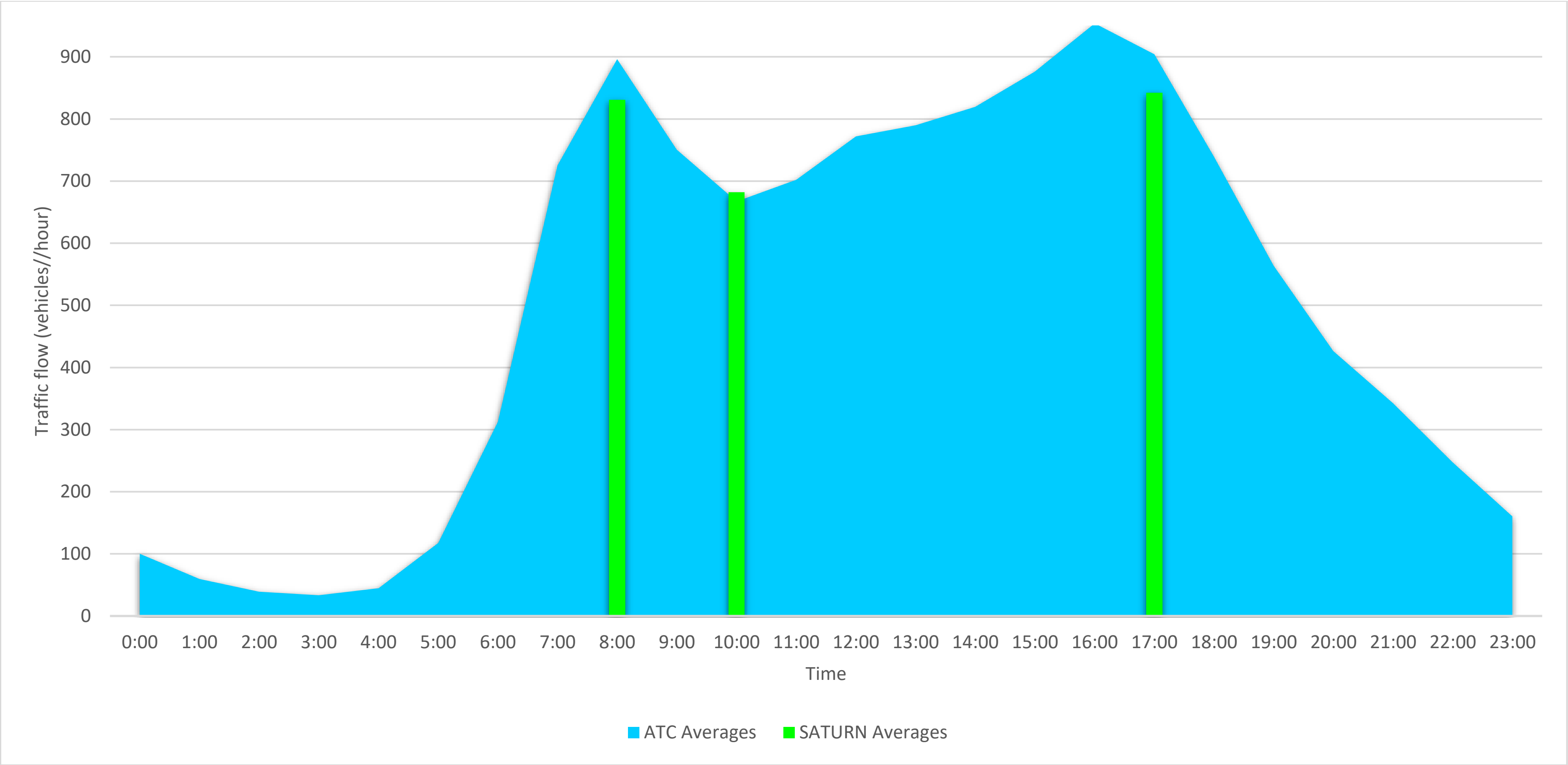


Figure 32 Average Hourly Traffic Flows in Bradford across 19 Automatic Traffic Counter (ATC) Locations (reporting on 35 directions) (blue) and Average Hourly Traffic Flows from SATURN across the Corresponding Road Links (AM peak, inter-peak and PM peak hours) (green), Source: Own Work (Excel)

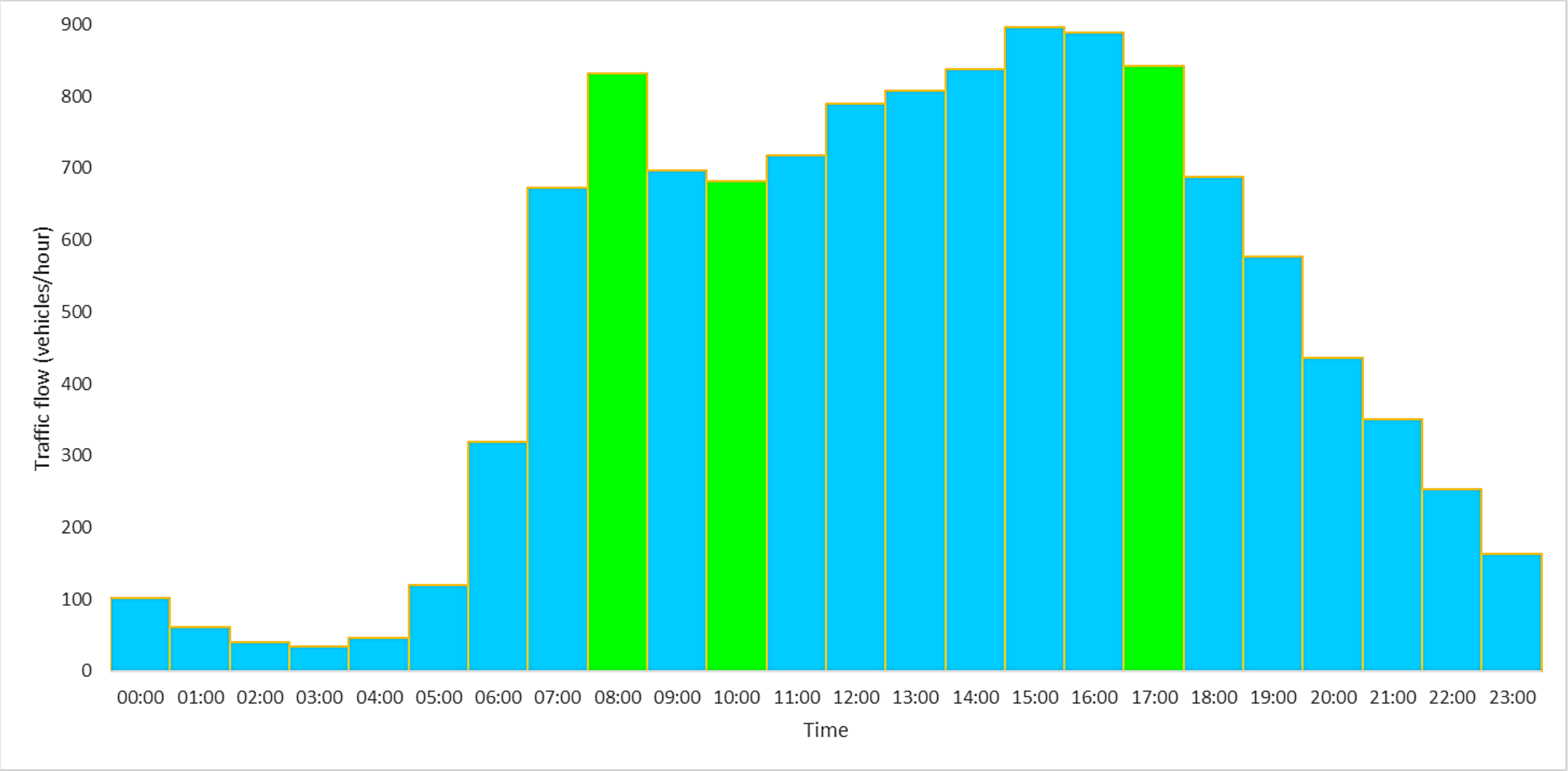


Figure 33 Weekday Link Average Diurnal Traffic Flows Modelled in SATURN (green) and complemented by Estimates Derived from Observed/Modelled Ratios and Observed Traffic Flows (blue), Source: Own Work (Excel)

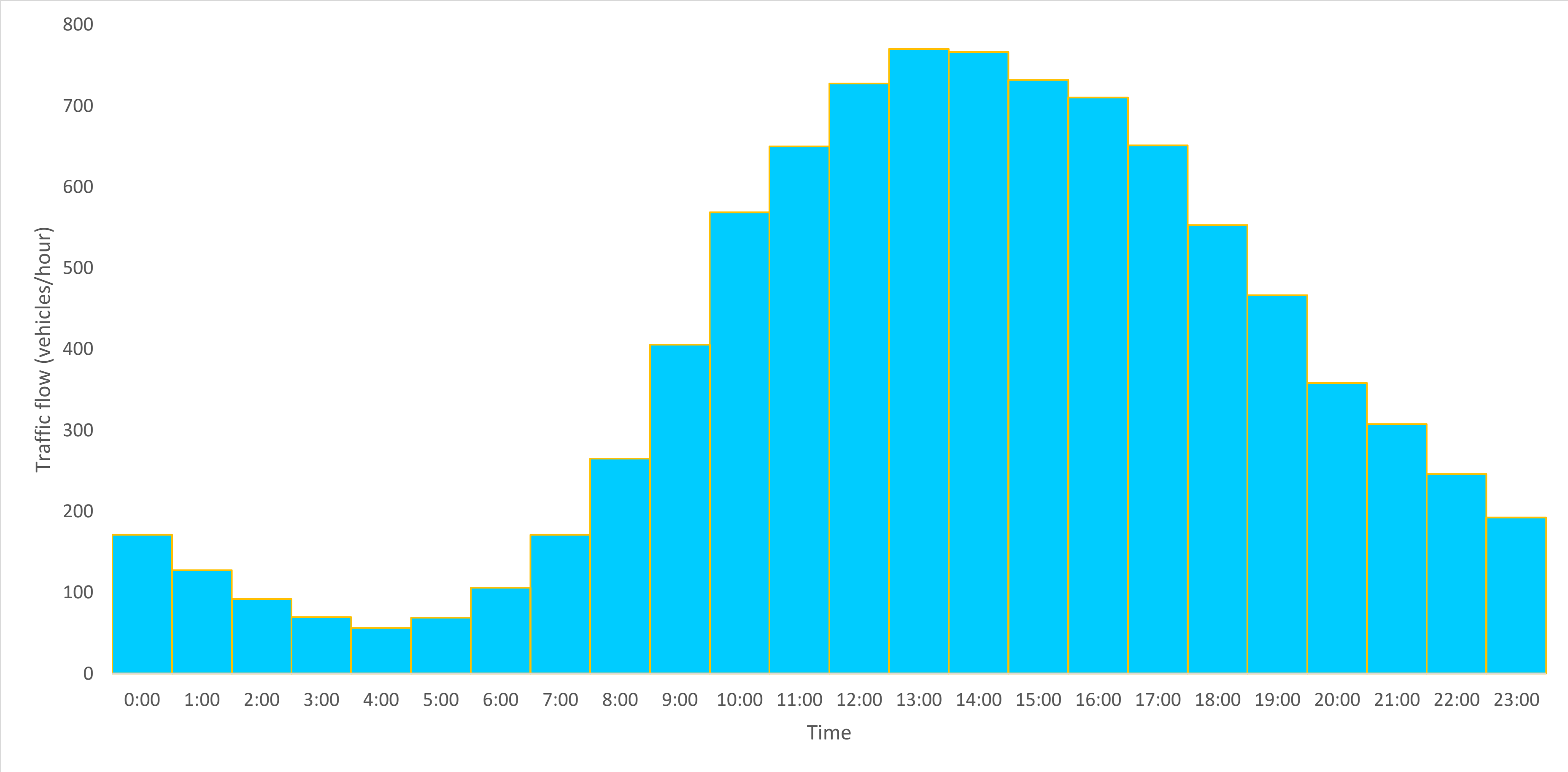


Figure 34 Weekend Link Average Diurnal Traffic Flows from Observed Traffic Flows (ATC Traffic), Source: Own Work (Excel)

3.5. Discussion

3.5.1. Summary

In this study, a previously developed and validated SATURN traffic model was obtained and run for year 2009 in Bradford (Steer Davies Gleave, 2009). The simulated road network covered a total of 4,500 road links and 696,880 vehicle kilometres (∑vehicles/h * link length in km). Traffic flows (PCU/h), and average traffic speeds (km/h) were estimated by the model and extracted at the road link level, for three simulated time periods: AM peak hour (08:00-09:00), inter-peak hour (the average inter-peak hour, 10:00-16:00); and PM peak hour (17:00-18:00). The link length (m) and the geographical locations of the SATURN nodes (X, Y coordinates) were also extracted for all links and plotted in ArcMap.

The SATURN model did not include separate vehicle user classes for passenger cars, LDVs, HDVs, buses or coaches and therefore these needed to be estimated. Traffic flows estimated in PCU/h were converted to traffic flows in vehicles/h, using PCU conversion factors originally used in the model's development. Flows in vehicles/h were then split into the different vehicle classes (e.g. diesel and petrol passenger cars, diesel and petrol vans (LDVs, three weight categories), diesel buses (single-decker and double-decker), diesel coaches (standard and articulated), and diesel rigid and articulated trucks (HDVs, various weight categories). Subsequently, the traffic flow of each vehicle class was split into the vehicles' EURO emission standards, catalyst status and after-treatment technology. The traffic split was done using standard published fleet proportions in England (National Atmospheric Emissions Inventory and Ricardo Energy and Environment, 2014). Previous traffic flow validation of this SATURN model was not independent i.e. the links used for the validation were used in the model's calibration as well, and therefore an independent validation exercise was undertaken. The validation results showed that the model performed reasonably well in estimating traffic flows, especially at the aggregate level, although the links variation was substantial in a select number of smaller/lower level roads, where the model tended to under estimate observed traffic flows.

As the SATURN model only simulated three time periods, traffic flows outside these simulation periods were estimated using available traffic count data and modelled flows. Using the traffic diurnal trends constructed from traffic counts at 19 ATC points in year 2009, modelled traffic flows in vehicles/h were scaled to obtain a diurnal hour-by-hour traffic flow profile, on an average weekday and weekend in 2009.

The results showed that the highest traffic flows were estimated in the AM peak, followed by the PM peak then the inter-peak period. Average traffic flows were highest in the PM peak, followed by the AM peak then the inter-peak period. Traffic speed results showed that the average link speed across the three simulated time periods was around 33 km/h, conveying the urban nature of the SATURN road network. Over 50% of all links in all time periods had speeds lower than 40 km/h. Conversely, less than 2% of all roads had speeds higher than 60 km/h. The link length statistics showed that a high proportion of the links were short. For example, 50% of all links were <172 m. These shorter links imply traffic and driving conditions that may be characterized by low average speeds and frequent stop-start driving typical on shorter sections of roads between junctions and crossing in urban areas, as opposed to free flow as would be expected on longer e.g. motorway road sections. The X and Y geographical coordinates extracted from the SATURN network and plotted in ArcMap revealed that although there was a topographical correspondence between the nodes in SATURN and the actual road locations in an underlying base map, these two did not accurately match and the SATURN nodes were not correctly spatially referenced. Overall, the SATURN network was a caricature and a simplification of the real road network. To improve the accuracy of the nodes and road links locations, all node coordinates which did not coincide with a road in ArcMap were snapped onto the nearest road using a snapping procedure developed in this study.

3.5.2. Strengths

The key strength of the current approach used to obtain traffic flow and average speeds is in its comprehensive and wide spatial coverage. The SATURN model used in this study covered 4,500 road links, which in turn covered a large extent of the Bradford metropolitan area (Figure 17). This extent of spatial coverage is not possible to achieve using observed traffic counts or speeds, as measurement points cover a limited geographical scale (Figure 11), often focused on major and strategic roads monitored for transport planning purposes, rather than environmental and exposure assessment purposes. A wide and comprehensive spatial coverage is particularly important in an exposure or health impact assessment study where the aim is to capture the spatial distribution and variability of exposures across the study population (Nieuwenhuijsen, 2015). The use of the counters can feasibly mask the variability in traffic levels and associated TRAP levels and therefore mask differences in exposures and associated health effects or impacts. There is also a compounded influence of air pollution originating from multiple, smaller and lower level roads combined. These exposures can have a different and additional effects on human health outcomes, when, for example, compared to exposures originating from major roads only (English et al., 1999, Perez et al., 2013).

A second strength of the current approach is that it allows estimating the specific contribution of the different vehicles to the overall TRAP exposures. As the vehicle classes in the traffic fleet were explicitly estimated, vehicle emissions can be assigned to each class's flow. This may help advance the understandings of the most polluting vehicle fleets and patterns of exposure and therefore add value to the efforts undertaken to identify the "right" sources to target. Currently, there is a widespread lack of full-chain health impact assessment characterizing the whole chain from emissions sources, to exposures, and finally to health effects and/or impacts; something which limits disentangling the health effects of TRAP from the health effects of other emission sources, and vice versa (Nieuwenhuijsen et al., 2017). This also limits the comprehensibility of, and confidence in recommending fleet specific and traffic planning or management specific interventions which would be valuable and desirable for policy makers (Nieuwenhuijsen et al., 2017).

In own work, the SATURN traffic flows were scaled across the full day to cover the remaining hours outside the model's simulation times (AM peak hour, inter-peak hour and PM peak hour). The use of the ATC traffic data for this purpose provided a realistic and an area-specific scaling factor to develop the traffic diurnal profile. Previous work in Bradford using SATURN model outputs in subsequent atmospheric dispersion modelling and health impact assessment only relied on the SATURN modelled traffic flows to represent a traffic and an emission diurnal profile (City of Bradford Metropolitan District Council, 2013); i.e. the SATURN modelled inter-peak hour traffic was allocated to all periods outside the simulation times (Crowther, 2016). As demonstrated from traffic flow observations shown in Figure 32, this assumption is not realistic, and this works contributes to a more realistic estimation of hour-by-hour daily traffic flows and emissions.

Further, the use of traffic speeds estimated from the model instead of using link speed limits/free flow speeds as was done previously in a dispersion modelling study in Bradford (de Hoogh et al., 2014), is considered an advantage as speed limits/ free flow speeds are usually not achieved in urban settings and congested times. Vehicle emissions are highest at lower average speeds, which incorporate frequent stop-start driving and high emitting events such as accelerations, and as such this work further contributes to a more accurate and realistic representation of vehicle activity and associated emissions in the study area.

Finally, the NAEI vehicle classes fleet split used in this work was compared to vehicle class proportions calculated from two other independent datasets collated over the same year: 2009 (CBMDC traffic counts at 98 locations and DfT traffic counts at 109 locations). The NAEI vehicle class proportions were considered satisfactorily similar and robust. The most uncertain estimates were buses and coaches and HDVs proportions, which were around 60% higher and 40% lower in the NAEI than in the other datasets, respectively (Table 14). These differences may be because the DfT and CBMDC would have undertaken their traffic counts on major and strategic roads and motorways only; likely to be carrying higher truck volumes and fewer buses than urban roads represented in the NAEI spreadsheets.

Table 14 Vehicle Class Proportions from Three Different Datasets

Vehicle classification	NAEI for Urban[a] roads (2009)[b]	CBMDC local classification between 0700-1900 (year 2009)[c]	Percentage difference	DfT[d] traffic counts (2009)[e]	Percentage difference
Cars and Taxis	82.6%	81.72%	+ 1.08%	81.77%	+ 1.02%
Buses and Coaches	1.55%	1.03%	+ 50.49%	0.91%	+ 70.33%
Light Duty Vehicles	12.54%	12.65%	- 0.87%	13.08%	+ 4.13%
Other Duty Vehicles	2.13%	3.79%	- 43.80%	3.57%	- 40.34%

[a] Assuming that urban roads are the most common in Bradford's simulated road network

[b] Proportions given by vehicle kilometres

[c] Counts made at 98 locations across Bradford

[d] Counts made at 109 locations across Bradford

[e] Proportions given in thousand vehicle miles

3.5.3. Limitations

Despite its strengths, the approach also has its limitations. First, the journey time validation of the model revealed that although the overall modelled journey times were within 15% of observed values, in line with established traffic modelling guidelines, modelled journey times were consistently faster than observed journey times, in all time periods. This suggested that congestion was underrepresented in the model, particularly in the morning peak hour (Steer Davies Gleave, 2009). These differences may be in part due to road capacity being over-represented in certain areas of the model and/or certain conditions that are inherently included in the average observed journey times, such as adverse weather conditions, road works and closures and motor vehicle crashes slowing down traffic, but not included in the model. The underrepresentation of congestion and lower average speeds in the network can be particularly problematic when estimating associated emissions; which tend to be higher at the lower average speeds with frequent stop-start driving (Chapter 4). Further, the SATURN model was found to under estimate traffic flows in the independent validation exercise, especially at the smaller road links.

Second, although there generally was good topographical correspondence between the nodes in SATURN and the actual road locations as identified from an underlying base map, these two did not accurately match and the SATURN nodes were not correctly spatially referenced. Contact with the CBMDC indicated that this SATURN model was developed prior to GIS use and application in the city council (the original network back in 2002), and the model was therefore intended to be a schematic representation of the network which was not correctly spatially referenced. The council is currently in the process of developing a new geo-referenced SATURN model, but this was not available during the period of this study. The geo-processing of the traffic network using snapping methods in this study is not ideal but was found to have slightly improved the layout/expected locations of the nodes, as identified by manual oversight. Both the geo-processed and the original SATURN network will be taken further in subsequent atmospheric dispersion modelling to explore the associated differences in the air quality estimates and their validation metrics.

Third, SATURN results in traffic flow and average speed data on a link basis, regardless of the link’s length or characteristics i.e. any link has one average speed which applies over the whole link and one traffic flow based on the AM peak hour, inter-peak and PM peak hour. This assumes that traffic flows and speeds are homogenous over the entirety of the links. The averaging of the speeds over a whole link is problematic, especially over longer links. Real-world traffic flows and particularly speeds are heterogeneous instead and the accuracy of emission models which utilize this data highly depends on the traffic model’s ability to capture speed fluctuations (Amirjamshidi et al., 2013). Furthermore, the average speeds obtained from the model were assumed to apply/be constant for all vehicle classes on the roads. In real-world driving, average speeds for different vehicle classes is not constant over the same route and can be highly variable (Mehar et al., 2013); for example consider buses or HDVs movement compared to passenger cars movement over the same routes. This assumption is a limitation in all current approaches, whether one uses data from mesoscopic traffic models such as SATURN or data from traffic counters and can mask a highly variable vehicle-class-specific traffic activity and associated emissions levels. It was not possible with current data and tools to account for the unusual driving patterns of some vehicle classes such as buses and taxis where stops and starts more frequent making their stop-start emissions higher not only because of the higher absolute magnitude of emissions during those events but also because of their higher occurrence frequency.

Further, other work has found that the Bradford fleet was markedly older than national averages; for e.g. in 2012, 49% of buses in Bradford were Euro III or older compared with 32% in Leeds (City of Bradford Metropolitan District Council, 2013). This latter difference, however, was unaccounted for in this study as the NAEI national average were the ones adopted to proportion the vehicle fleet mix.

Finally, although this approach incorporated many more roads than e.g. using traffic counters, it did not cover all streets on the urban network. The most minor roads e.g. cul-de sacs feeding into a more major road were often agglomerated into a single link and not represented individually, possibly leading to some exposure misclassification and a further under estimation in overall traffic levels and subsequently associated emissions.

3.5.4. Avenues for Future Work and Next Step

To estimate the air quality profile and the childhood population exposures to TRAP in the study area, it is possible to link the hour-by-hour traffic flows and average speeds estimated in this research phase to average-speed-emission functions/models, introduced in the next chapter (Chapter 4) and subsequently to air pollution dispersion models (Chapter 5), creating a full-chain exposure model. The next steps of this study will aim at developing a set of more reliable and Bradford-tailored average-speed emission functions and then knitting together these multiple data sources and models for later full-chain health impact assessment. Specifically, the traffic flows and average speeds estimated in this research phase will be used as inputs to the newly developed and the standard (sourced from COPERT 4 v 10) average-speed emission functions to estimate a Bradford road vehicle emission inventory for year 2009. Both the original and the geo-processed traffic networks will be used in the final dispersion modelling to explore the impact of the spatial network editing on the air quality estimates and their validity.

Future work could usefully focus on using different traffic activity data sources for the compilation of emission inventories and later exposure assessment exercises. For example, GPS fleet tracking datasets such as Teletrac can be used. Such datasets are expected to provide a higher temporal resolution and a more realistically variable speed profiles over smaller pieces of the links/roads in Bradford and one that is specific for the different vehicle classes. Future work can also explore the effects of a differential fleet mix on the different road types (e.g. urban versus motorways) to test the sensitivity of the exposure estimates to the fleet mix proportions.

Further, continuous communication with the CBMDC revealed that transport planning, environment and health departments at the city council level are poorly coordinated and integrated. The transport planning unit in CBMDC developing and updating traffic models for Bradford appear to work in isolation and not to consider how their work can be integrated in wider environmental and health impact assessments for proposed transport planning schemes. For example, the nodes in the SATURN model were not correctly geo-referenced and this is thought to be due to its aims and key applications as a transport planning tool that analyses and evaluates traffic management scheme and (changes in) traffic flows and *not* exposures, environmental or health impacts. This issue was found to limit the SATURN usability for environmental, epidemiological or health impact assessment applications. Better coordination between these departments would improve the utility of their datasets and models for future applications of this nature.

4 Vehicle Exhaust Emission Modelling

4.1. Background

4.1.1. Vehicle Emission Factors

To evaluate the health and environmental impacts of traffic activity, vehicle emissions need to be quantified. In this study, the focus was exhaust gas emissions of Nitrogen Oxides (NO_x). NO_x is a specific marker for TRAP, especially diesel vehicles exhaust, and can be readily converted to Nitrogen Dioxide (NO_2) using published conversion factors. Vehicle particle emissions were not considered in this study, due to multiple reasons. First, Particulate Matter (PM) exhaust measurements are inaccurate as they are performed by trapping exhaust particle emissions over a test using particles filters which are imprecise (DieselNet Technology Guide, 2012), partly due to the (semi) volatile PM fraction present in the exhaust gas. The mass trapped on the particles filters is then factored by the second-by-second Particle Numbers (PN) exhaust measurements made over the same test. These factored values are used in constructing vehicle emission maps for emission modelling software such as PHEM, the results of which have showed that PM estimates are unreliable and are significantly worse than gaseous emission estimates such as NO_x (Section 4.3.5). Second, there are issues with modelling PM at the air quality estimation stage as current dispersion models are an oversimplification of the processes particles undergo in the atmosphere including accumulation, deposition and atmospheric chemistry reactions, partly because exhaust PM is not well-defined. Other significant sources of traffic-related PM including brake and tire wear, road abrasion and resuspension, which are problematic to quantify (Thorpe and Harrison, 2008), cannot be taken into account in the modelling practice of this study.

Typically, vehicle exhaust emissions are expressed as mass emissions per unit distance (Equation 4.1.); mass emissions per unit time (Equation 4.2.) or mass emissions per unit fuel consumed (Equation 4.3.) (Tate, 2014b).

$$\text{Emission per Unit Distance} = \frac{\text{Amout Emitted (g)}}{\text{Distance Travelled (e.g. km)}} \ldots \text{(Equation 4.1.)}$$

$$\text{Emission per Unit Time} = \frac{\text{Amount Emitted (g)}}{\text{Time Taken (e.g. seconds)}} \ldots \text{(Equation 4.2.)}$$

$$\text{Emission per Unit Fuel Consumed} = \frac{\text{Amount Emitted (g)}}{\text{Fuel Consumed (e.g. litres of fuel burnt)}} \ldots \text{(Equation 4.3.)}$$

These three expressions are referred to as vehicle ***emission factors***. Vehicle emission factors are the data underlying national emission inventories and subsequent dispersion modelling. In practice (when performing analytics of commonly available traffic data), the most commonly used and referred to vehicle emission factor is that per unit distance (Equation 4.1.) (i.e. g/km). Whenever the term emission factor (EF) is used in this work it will refer to a distance based vehicle emission factor in g/km, unless otherwise stated.

4.1.2. Review of Vehicle Emissions Measurement and Modelling

Exhaust gases are comprised of a complex mixture of combustion products, un-burnt fuel and water vapour, produced as by-products when engines are in operation. There are three types of emission sampling and measurement techniques which are commonly used: engine dynamometer testing, chassis dynamometer testing and on-road measurements (Tate, 2014a). Each method has strengths and limitations.

Both dynamometer tests, chassis and engine, are laboratory-based, with strict operating conditions, defined equipment and highly controlled environments. These tests are therefore highly replicable and well suited for regulatory certification, type approval and comparative testing (Pelkmans and Debal, 2006). In an engine dynamometer test, a vehicle engine and associated components are connected to a dynamometer, which imposes a load on the engine. Commonly, the dynamometer runs the engine at steady state speed. Transient dynamometers, which can run the engine through a series of varying driving events including acceleration, deceleration, idling and cruising are more complex and costly and therefore are scarce. As the cost of acquiring and installing engines is high, engine dynamometer testing is primarily used for research and development purposes (Tate, 2014a). In a chassis dynamometer testing, a whole test vehicle is connected to a dynamometer which imposes loads on the rolling road the vehicle rests on and runs the engine through a series of varying driving events including acceleration, deceleration, idling and cruising. Unlike engine dynamometer, chassis dynamometers are set up for testing multiple vehicles, but are more complex and costlier to operate (Tate, 2014a). Overall, the main criticism of dynamometer testing lies in the fact that laboratory testing procedure and environments do not adequately represent real-world driving conditions and environments, which vehicles perform in daily. Driving cycles used in emission measurements and testing such as the New European Driving Cycle (NEDC) and the Common Artemis Drive Cycle (CADC) have been repeatedly criticized because of their significantly different vehicle dynamics when compared to real-world driving (Ropkins et al., 2009, Barlow et al., 2009). These differences include differences in acceleration, deceleration and speed which are less transient in these cycles when compared to real-world driving (Barlow et al., 2009, Chen and Borken-Kleefeld, 2014, Pelkmans and Debal, 2006). Vehicle specific power is lower in these cycles compared to real-world driving (Chen and Borken-Kleefeld, 2014). Laboratory environment conditions such as the absence of road gradient, wind (Transport and Environment, 2013) extra vehicle weight (The International Council on Clean Transportation, 2015), and the controlled temperature and humidity (Martini et al., 2012, Department for Transport, 2016b, Pelkmans and Debal, 2006), also mean that these real-world driving factors are not being accounted for, despite their important impacts on engine load and associated emissions. For example, CO and NO_x real-world emissions from a EURO 4 compliant vehicle model year 2000, may be up to 10 times higher in real traffic compared to the NEDC cycle (Pelkmans and Debal, 2006).

The third type of emission measurement techniques are on-road measurements. As the name suggests, on-road emission measurements are made in real-world driving conditions when the vehicle is in operation and include ‘in traffic’ or ‘in situ’ methods (Ropkins et al., 2009). ‘In traffic’ methods include using Portable Emission Measurement Systems (PEMS) mounted onto the back of the vehicle and directly measuring its exhaust emissions (Weiss et al., 2012, Liu et al., 2009, Kousoulidou et al., 2013), or equipping another vehicle with emission measurement devices (mobile laboratory) and having it follow the vehicle under investigation; sampling emissions from a chased vehicle (Zavala et al., 2006, Shorter et al., 2005, Saari et al., 2016). ‘In situ’ methods include using road tunnel or road side monitoring equipment such as Remote Sensing Device (RSD) to measure emissions (Ropkins et al., 2009, Carslaw et al., 2011a). The key strength of all these methods lies in the actual measurement of vehicle emissions under real-world driving conditions and in real-world environments. The key limitation is that real-world driving is non-standardized and it is often not possible to perform multiple standardized tests using these techniques, increasing uncertainty compared to laboratory-based measurements. Furthermore, there are practical limitations in setting up the equipment, power sources and in the high costs associated with these equipment and measurement campaigns, which often leads to small sample sizes (Tate, 2014a).

As vehicle emission monitoring is very limited in space and time, modelling approaches are used to fill the gaps where monitoring is unfeasible and provide information used for compiling national and regional emission inventories. The main practiced methodology used for estimating vehicle EFs, for a certain pollutant and a given vehicle class/technology, is based on the notion that vehicle EFs are functions of the average vehicle speed over 'a trip' (Equation 4.4). As such, if the average speed of a vehicle over a trip is known (e.g. through traffic models or measured data), this value can be plugged in a corresponding average-speed-emission function, specific to a pollutant and a vehicle class/technology, to obtain an EF for that vehicle; pollutant and at that average speed for the trip.

$$\text{Emission per Unit Distance}\left(\frac{\text{g}}{\text{km}}\right) = f\,(\bar{\text{v}}) \ldots (\text{Equation 4.4.})$$

Where $\bar{v}$ is the vehicle's average speed.

This is currently the standard approach adopted in vehicle emission modelling (Barlow and Boulter, 2009). In the UK, EFs for road transport are defined as functions of the average vehicle speed, over 'a trip' (Barlow and Boulter, 2009). Initially, NO_x average-speed-emission functions were developed by Transport Research Laboratory (TRL limited) at the request of the UK Department for Transport (DfT) (Boulter et al., 2009), using a large database of emission and speed measurements conducted in the laboratory (these functions are referred to as TRL/DfT functions). Subsequent updates to these functions were undertaken and reported in Li et al. (2009c).

After 2011, new functions replaced the TRL/DfT functions when the UK emission factor toolkit switched to using average-speed-emission functions sourced from a regional European emission model referred to as COPERT: COmputer Programme to calculate Emissions from Road Transport (Department for Environment Food and Rural Affairs, 2016b, Department for Environment Food and Rural Affairs, 2014c). The reason behind this switch/ revision was emerging evidence that there is lack of consistency between the trends of road transport NO_x emissions estimated by current functions and the trends in ambient roadside NO_x concentrations measured in the UK (Carslaw et al., 2011a). Additionally, NO_x emissions for some modern vehicle classes obtained from the previous average-speed-emission functions, especially diesel fuelled ones, did not reflect higher real-world emissions as recorded by on-road emission measurements (Passant et al., 2012, Carslaw et al., 2011a). The UK's switch to using COPERT was also perceived as an advantage as it is the standard methodology used by EU member states, making UK emission estimates more comparable and consistent with other countries. The COPERT model also assumes the average-speed-emission functions methodology accepting that vehicle EFs are functions of the vehicle’s average speed, over a trip. The model’s development is coordinated by the European Environment Agency’s and the European Commission’s Joint Research Centre (European Research on Mobile Emission Sources Group, 2016). COPERT contains some of the most widely used average-speed-emission functions, worldwide (Barlow and Boulter, 2009) (Figure 35) and is used by most European countries in official reporting of national emission inventories for road transport (Kousoulidou et al., 2010). A small number of European countries use EFs from the Handbook of Emission Factors for Road Transport (HBEFA), which was developed on behalf of the Environmental Protection Agencies of Germany, Switzerland and Austria (HBEFA, 2016). Emission models estimating EFs as functions of average speed over a trip are also used worldwide e.g. in the USA (Koupal et al., 2010) and New Zealand (Sridhar et al., 2014).

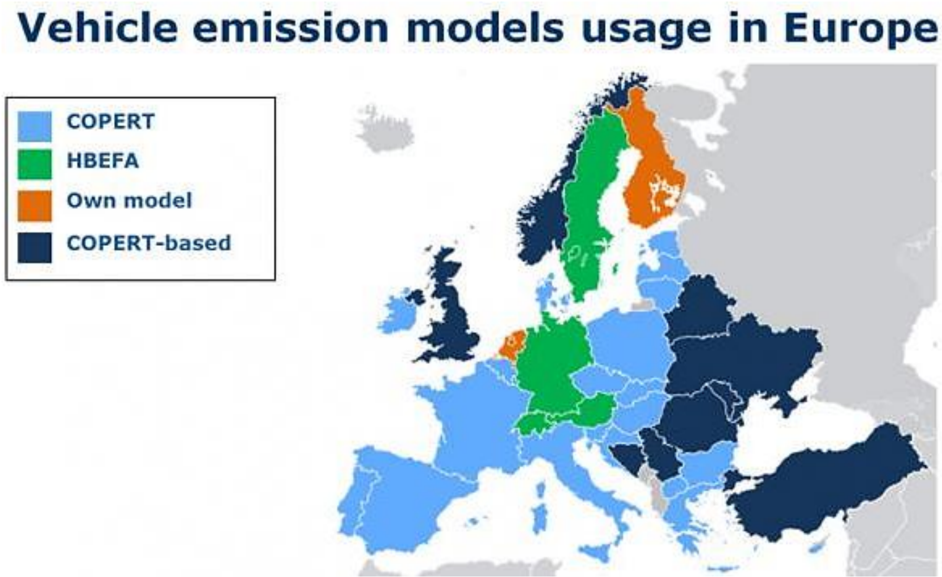


Figure 35 Leading Road Vehicle Emission Models Used in Europe, Source: European Research on Mobile Emission Sources Group (2016), Source: http://www.ermes-group.eu/web/leading_EU_models

EFs and emission estimates derived from this methodology are widely accepted and used in numerous databases and important policy making tools such as the NAEI, the London Atmospheric Emission Inventory (LAEI), the UK DfT Local Authority Carbon Tool (Barlow and Boulter, 2009, Williams et al., 2011, Transport for London, 2015), and the National Transport Model (NTM) which is the UK DfT’s main strategic policy testing and forecasting tool (Li et al., 2009a). Importantly, average-speed-emission functions are also incorporated in many local air pollution dispersion models, which combine the EFs functions and the dispersion modelling software into a single package (e.g. ADMS-Urban) (Barlow and Boulter, 2009).

Although there are intrinsic limitations that come with 'simply' modelling vehicle emissions based on average speeds (Barlow and Boulter, 2009), traffic data and models typically only provide average speeds for road links. Air pollution dispersion models can only take average speeds at the link level as inputs for calculating link-based emission rates using built-in EFs. Therefore, both systems are configured to fit this modelling approach and hence it was followed. Modelling vehicle emissions based on more meaningful predictors, such as vehicle specific power (Jimenez-Palacios, 1998, Carslaw et al., 2013), is currently unfeasible, if the outputs are to be linked to macro or meso scale traffic network data and subsequent dispersion modelling, as in this study. There are, however, numerous limitations associated with the standard average-speed-emission functions, especially in how these were developed (Section 4.1.3). This work will fill some of these gaps while retaining the premise and practicality of vehicle emission modelling based on average speeds.

4.1.3. Underlying Data and Limitations in Current Average-Speed-Emission Functions

Despite being widely used in numerous applications, the COPERT model has important limitations that arguably make its emission estimates unreliable, especially at lower average speeds which are frequent in urban driving (Tate, 2015a). Average-speed-emission functions given in COPERT are based on a wide range of national and regional average-speed-emissions data collected from laboratory vehicle tests (Kay, 2013, Li et al., 2009b). This data is based on the results of thousands of empirical tests which have been conducted through several projects and initiatives across Europe, over many years (Ntziachristos, 2016a). Perhaps because of this, there is lack of clarity about the exact data underlying, and the methods used to establish, COPERT's average-speed-emission functions (Tate et al., 2016).

The average-speed-emission functions given in the COPERT model are developed by corroborating average speed and emission factors functions. Functions are developed by calculating the average EF over a trip from a drive-cycle (transient test) and relating this to the average speed of the trip. The general premise of this method is as follows: a vehicle of a certain type/technology is driven over a driving cycle (or a speed profile) in the laboratory. In theory, the driving cycle is selected to represent real-world driving conditions (e.g. CADC) rather than cycles used for regulatory compliance (e.g. NEDC). However, the choice of driving cycles remains unclear, and these do not reflect local driving conditions in study areas where functions will be used. As the vehicle drives over a specified cycle, its exhaust emissions are being measured in the laboratory. The driving cycle is then split into trips (i.e. sub-cycles), and the average emission level recorded at each trip is associated with the average speed recorded for each trip. Each average speed and average EF are paired and constitute one data point. Multiple tests are undertaken for each vehicle type/technology such as diesel and petrol passenger cars, vans, trucks, buses and coaches to produce more data points. These data points are then plotted and serve as the underlying data to construct a function relating the recorded vehicle's average speed (x; predictor variable) to the recorded average EF (y; response variable), at the trip level (Ntziachristos, 2016b). The definition of a trip in this context, however, remains unclear and is not standardized. For example, a trip can be the whole driving cycle, or can be the time being driven in a certain driving condition such as urban, rural or motorway driving. This process is illustrated in Figure 36.

This approach has intrinsic limitations. First, there is no conceptual rationale for the averaging periods at which a 'trip' is defined. As vehicle emissions are episodic in nature and significantly fluctuate over very short time periods (i.e. seconds) (Frey et al., 2003, Ropkins et al., 2007), averaging speeds and corresponding EFs over long 'trip' intervals can be problematic as the longer duration trips averages will mask small-scale variations in real-world driving emissions. Peak emission rates occur during short-term, high-power acceleration events (Frey et al., 2003); for example after junctions (Daham et al., 2009) or traffic lights, and are typically associated with lower average speeds (O'Driscoll et al., 2016). Previous research showed that average emissions of several exhaust pollutants during acceleration are an order of magnitude larger than during cruising (Ritner et al., 2013); and that low average speeds are associated with the worst emitting NO_x sub-trips (O'Driscoll et al., 2016). If such polluting short events and sharp peaks are not adequately incorporated and represented in the average-speed over a trip, then average emissions calculated for this trip are expected to be lower than in real driving, particularly in the context of urban driving where stop-starts are frequent and road link are short with higher speed fluctuations.

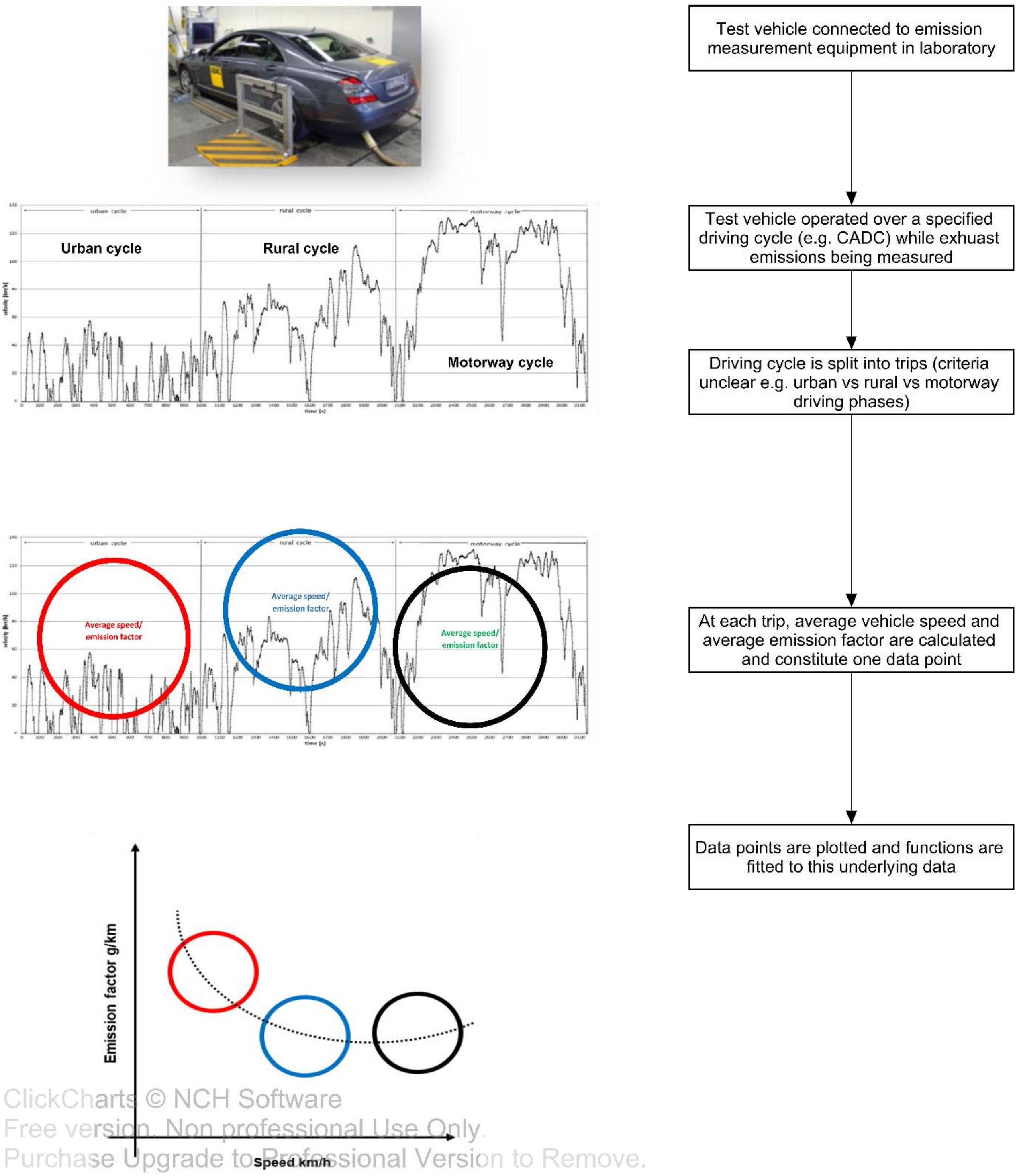


Figure 36 COPERT Average-Speed-Emissions Functions Derivation, Source: Own Work (NCH Software)

Second, using laboratory emissions measurements to accurately estimate real-world vehicle emissions has proved problematic, as driving and testing conditions in numerous laboratories do not represent real-world vehicle use. Emission models solely based on laboratory emission measurements can significantly under estimate vehicle emissions as car manufacturers optimize (Boulter et al., 2007), and manipulate (e.g. dieselgate emission scandal) (Schiermeier, 2015) fuel consumption and exhaust emissions control based on testing conditions. If the measurements underpinning the models are flawed, then the output of the modelling is expected to be inaccurate. Example of important flaws in laboratory testing conditions include the fact that driving cycles are effectively performed over a flat road, in the absence of wind (Transport and Environment, 2013) and extra vehicle weight (The International Council on Clean Transportation, 2015), and in controlled indoor environments of certain temperature and humidity (Martini et al., 2012, Department for Transport, 2016b). These parameters vary and fluctuate in the real-world and have a significant influence on engine power and real-world exhaust emission (Barlow and Boulter, 2009, Boriboonsomsin and Barth, 2009, Boroujeni and Frey, 2014, Westcott, 2016, Sayegh et al., 2016). For example, Zhang and Frey (2006) recorded an increase in CO_2 emission of 40-90% for three light duty gasoline vehicles over road sections with grade $\geqslant$ 5% when compared to road sections with grade $\leqslant$ 0%; Frey et al. (2008) recorded a 20% increase in localized NO emission rates with positive road gradients. Weilenmann et al. (2009) observed an evident increase in NO_x for diesel EURO 4 passenger cars as the air temperature decreased; Dardiotis et al. (2012) observed higher NO_x emissions at -7 °C compared to at 22 °C for most of their laboratory tested petrol vehicles with EURO 5 emission standards; and a new study by Emission Analytics tested 213 models across 31 manufacturers and measured a significant rise in NO_x emissions as temperature dropped below 18 °C (Westcott, 2016).

As such, vehicle emissions data obtained from laboratory measurements will result in an under estimation of real-world on-road emissions. As these factors (stop-start driving and frequent acceleration events, real-world driving conditions including road grade, extra load, temperature, humidity, wind etc.) do not adequately underpin laboratory emission testing procedure and therefore any vehicle emission model established on their data, the validity of the COPERT and similar models is questionable. In part, this may explain some of the inaccuracies associated with these models, especially in urban driving and at lower average speeds (Tate et al., 2016); a state typical in congested traffic and incorporates high proportions of idling, stop-start driving and cold starts.

Third, the statistical construction of the functions relating vehicle average speed to the average EF recorded can be based on a limited number of observations and insufficient sample sizes that differ depending on the number of measurements available for specific vehicle classes. For example, older vehicles with e.g. pre-EURO emission standards and newer vehicles with e.g. EURO 6/VI emission standards were either operating before comprehensive emission measurement campaigns were underway (pre-EURO, before July 1992) or just penetrated the market (EURO 6/VI, after September 2014), and therefore do not have comprehensive sample sizes. Further, functions are being fitted, even when there is high variability in the experimental data (Figure 37). No goodness of fit or error statistics are being reported alongside these functions and as the underlying data is largely unknown, it is difficult to judge the goodness of fit for a given function.

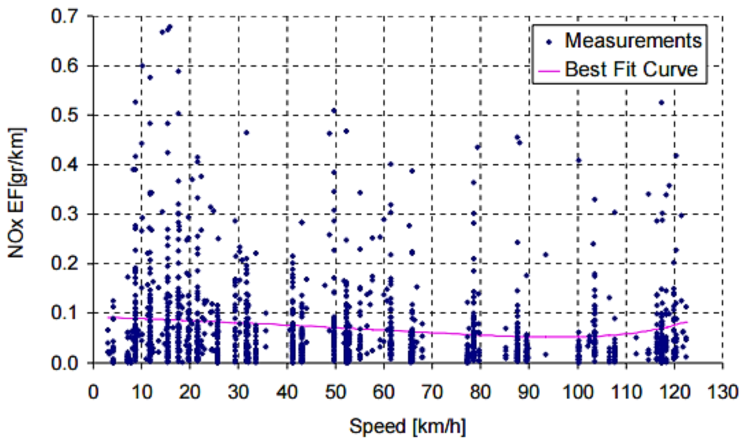


Figure 37 Example of Variability of Individual Measurements for the Derivation of Emission Factors (averaging approach unclear). Gasoline EURO 3 Passenger Cars, Source: ARTEMIS database reported in Kouridis et al. (2010)

Finally, there is evidence that COPERT becomes unreliable when moving to high saturation and short road sections. As a general guidance, COPERT's reliability is considered to increase as the link length increases to above 400 m (Samaras et al., 2014). As the link length increases, the likelihood that the data is dominated by a particular driving phase i.e. acceleration, cruise, deceleration decreases. Emission rates clearly vary substantially between these phases, with fuel burnt and associated air quality pollutant emissions highest during more power demanding acceleration phases. During deceleration phases emissions can for example fall to zero in modern vehicles with full cut-off strategies (Tate, 2015a). Therefore, the scatter in the average-speed and emissions data increases as links shorten and the predictive performance of a fitted function becomes substantially weaker. This is significant as for e.g. over 80% of all simulated links in Bradford are less than 400 m in length, whilst less than 20% are greater than or equal to 400 m in length (Chapter 3).

4.1.4. COPERT Validation

Although there is limited and partial literature relating to the validation of road vehicle emission models (Smit et al., 2010), a few studies investigating COPERT indicate important and systematic inaccuracies in its NO_x emission estimates. For example, a validation of COPERT with real-use on-road data showed that NO_x emission levels of a EURO 5 compliant diesel passenger car measured by PEMS were almost 60% higher than COPERT values (Kousoulidou et al., 2010). For a EURO 5 diesel passenger car, the mean values for the EFs calculated from the PEMS data and those estimated by COPERT for corresponding average speeds were found to deviate by 80%, 73% and 61% for a 10-km, 5-km and 1-km distance split, respectively, with the trend of COPERT under estimating NO_x (Dilara et al., 2010). For EURO 2, 3 and 4 diesel passenger cars, the ratio between the modelled and the observed NO_x emissions were found to be 61%, 71% and 77%, respectively in an on-road remote sensing measurement campaign in Sweden (Sjödin and Jerksjö, 2008). Another similar study found that COPERT was systematically underestimating NO_x emissions generated by EURO 3 petrol vehicles and pre-EURO to EURO 3 HDVs, where the remote sensing measurements consistently yielded higher emissions (Ekström et al., 2004). For diesel cars, the authors found that the remote sensing measurements were generally lower than COPERT III predictions for the older technology classes (pre-EURO and EURO 1), but higher for the newer technology classes (EURO 2 and EURO 3). In an on-road emission measurement study which analysed emission data collected from ≈72,000 individual vehicles using a vehicle emission remote sensing detector technique; the trend visible was that remote sensing measurements of NO_x were almost consistently higher than emissions estimates obtained from the models, across most vehicle categories including diesel and petrol passenger cars, the new generations of diesel LDVs and diesel rigid HDVs (Carslaw et al., 2011a).

These findings can, in part, explain the difficulty in matching real-world measured ambient air pollution concentrations with modelled ambient air pollution concentrations when COPERT emission estimates are utilized as inputs to air pollution dispersion models (Williams et al., 2011). The lack of decrease in ambient concentration of NO_x and NO_2, in clear disagreement with emission inventory projections, can in part also be attributed to these inaccuracies (Carslaw et al., 2011b, Beevers et al., 2012, Ekström et al., 2004). Some of these drawbacks have been identified by the COPERT developers and the model has recently undergone updates increasing some of HGVs NO_x EFs (European Environment Agency and EMISA S.A., 2011), and suggestions to uplift EFs for the newer generations of LDVs by up to 50% (EMISA S.A., 2015). As such, there is a need for new methods to estimate road transport emission inventories more accurately, particularly in urban driving.

4.2. Chapter Objectives and Contribution to Literature

The objective of this research phase was ***to develop a set of new average-speed-emission functions which are transparent, replicable and underlined by known data of better capability to capture real-world, local driving patterns and the high level of emissions associated with low average speeds*** (resulting from stop-start driving, shorter links and congested traffic states). As such, this research phase contributed to overcoming some of the limitations associated with the standard vehicle emission modelling approach and is expected to improve the accuracy of subsequent air pollution dispersion modelling, which will be undertaken to estimate the air quality profile and the childhood population exposure to TRAP within Bradford for a health impact assessment.

4.3. Methods

The overall methodology used in this work to derive new average-speed-emission function is illustrated in Figure 38 and overviewed next. In summary, 30.5 hours of real-world driving over Bradford, UK, were undertaken in an instrumented vehicle, which logged its instantaneous speeds over the tracked journeys. The collected instantaneous speeds were fed into the instantaneous emission model PHEM which estimated the second-by-second emissions of NO_x for 167 vehicle types and EURO emission standards. Using these outputs and following a novel micro-trip approach which splits the driving cycles into driving events between adjacent stationary periods (stop-start), new vehicle average-speed-emissions functions were developed.

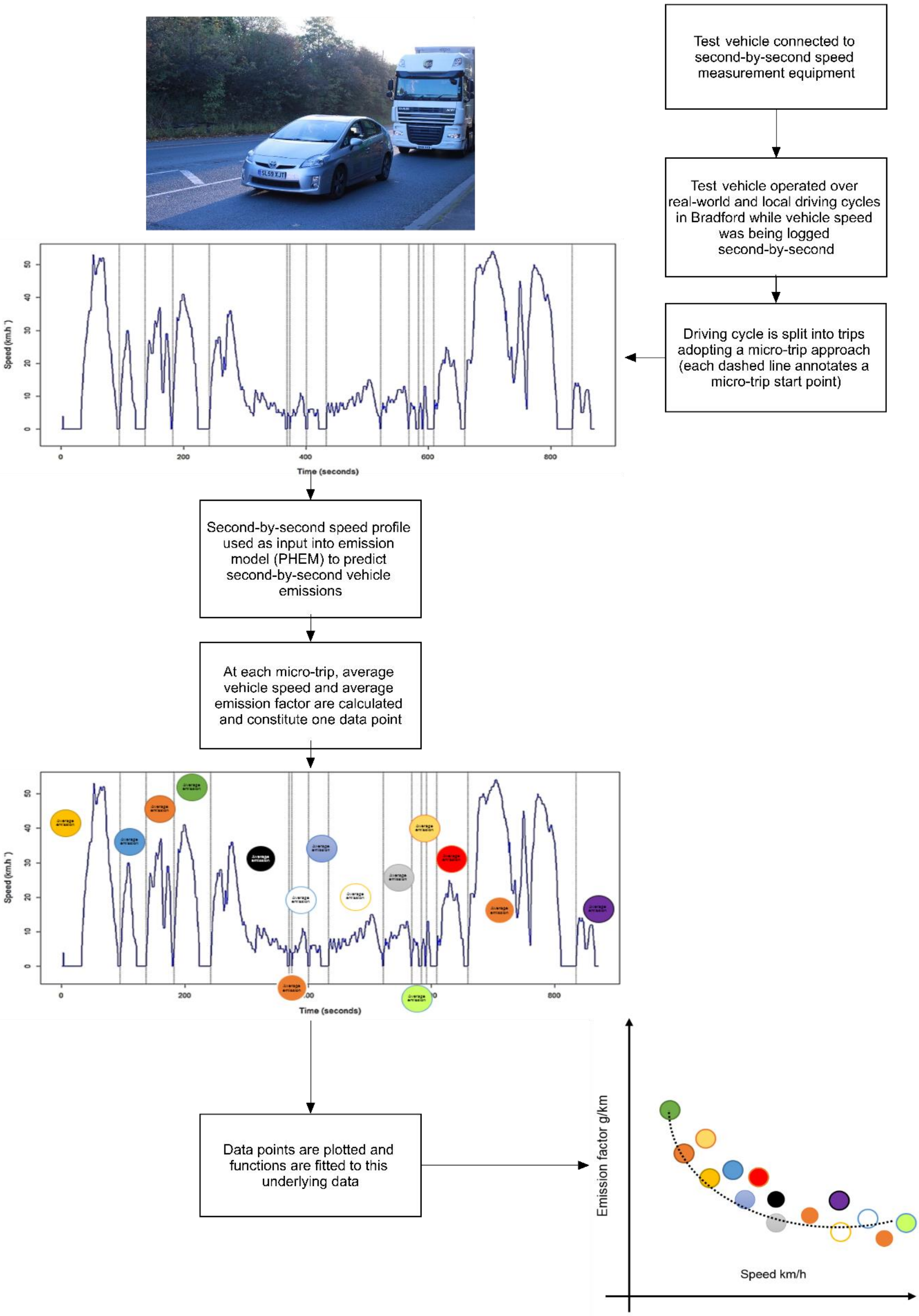


Figure 38 Average-Speed-Emissions Functions Derivation, Source: Own Work (NCH Software)

Collection of Real-World Driving Cycles

4.3.1. Test Vehicle and Instrumentation

The instrumented vehicle that was used to log second-by-second (instantaneous) speed profile over test routes was a 2009, EURO 5 emission compliant hybrid petrol Toyota Prius with a 1.8 Litres (1798 cc) engine and a 1370 kg kerb weight. The vehicle is shown in Figure 39. The instrumented vehicle was purchased and developed by Riley (2016) and more detail on its specifications is in Riley and Tate (2016).

Figure 39 The Instrumented Vehicle Surveying Tong Street, Bradford (12th October 2015), Source: Own Work (Camera picture)

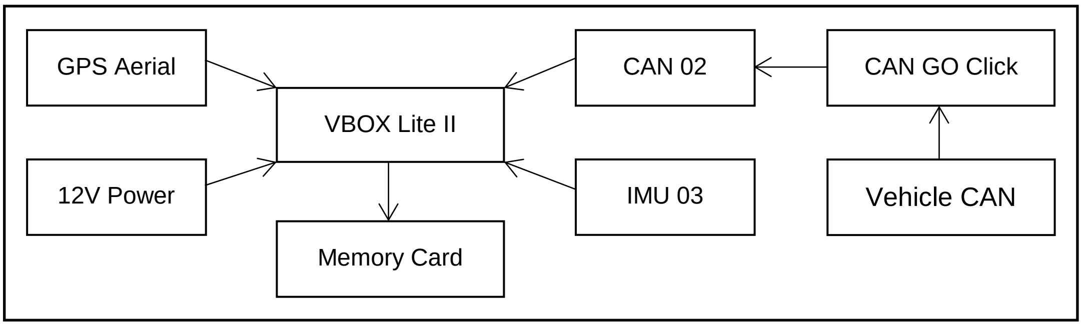
The vehicle was fitted with a portable activity monitoring system, which contained two data loggers, one from RaceLogic (https://www.vboxautomotive.co.uk/index.php/en/) and a second from HEM Data Corporation (http://www.hemdata.com/):

1. The RaceLogic VBOX II Lite GPS data logger (Version 2.3a) (VBOX Automotive, 2016) (Figure 40 a) was connected to the vehicle's 12V power socket in the vehicle's central compartment between the two front seats. The logged data was stored onto a 2GB compact flash memory card and was downloaded and backed up after each survey day.
2. The HEM Data DAWN On-Board Diagnostics (OBD) Mini logger (HEM Data, 2016) (Figure 41) was plugged directly into the vehicle's OBDII port under the steering wheel to the right. This data logger did not require a separate power

source. The logged data was stored onto a 32GB microSD memory card and was downloaded and backed up after each survey day.

At 2 Hz, the RaceLogic system measured and recorded the vehicle's speed based on satellite position data. In addition, it recorded speed measured by the wheel sensors on the vehicle's four wheels (referred to as 'wheel speed' data), and by acquiring Controller Area Network (CAN) bus data (referred to as 'vehicle speed' data). The CAN module was connected to the vehicle's CAN via a CAN GO Click connector that was clipped to the two CAN wires behind the vehicle's dashboard. The RaceLogic setup is shown in Figure 40 b. Similarly, at 2 Hz, the OBD acquired CAN bus data and recorded the vehicle's speed.

a) RaceLogic VBOX II Lite GPS Data Logger, Source: RaceLogic (2013)



b) RaceLogic Module Setup, Source: Riley and Tate (2016)

Figure 40 RaceLogic System

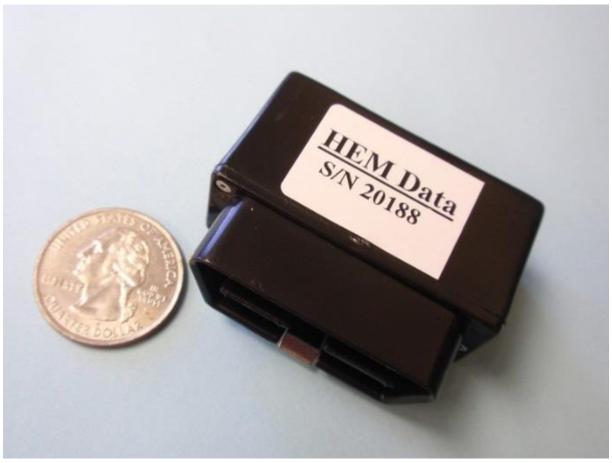


Figure 41 The HEM Data DAWN OBD Mini Data Logger, Source: HEM Data (2016)

4.3.2. Test Routes and Study Area Coverage

To collect a real-world representative second-by-second vehicle speed profile, multiple roads on Bradford's road network were used as test routes. A Fieldwork Risk Assessment (Low Risk Activities) was completed and submitted to the author's department. Test routes were driven on by the instrumented vehicle described above, which logged its second-by-second speeds over the driving course. The author initially selected test routes by inspecting a map of Bradford's road network and selecting apparent major/main roads (e.g. Bradford's Ring Road). Routes selections were finalized after the author consulted with the City of Bradford Metropolitan District Council (Jones, 2015).

The selected routes are shown in Figure 42 and encompass different road types including arterial roads into and out of Bradford including the A650 and Tong street (south-east); Bradford Road and Leeds Road (east-north); Keighley Road; Bradford Road and Bingley Road (north-west), Bradford's Ring Road, in addition to areas surrounding and within the inner ring road; the area around the M606 and the area surrounding Shipley and Saltaire and Keighley which suffer from the highest NO_x concentrations (Fielding, 2012).

Test routes were driven by three commissioned drivers with different driving styles and no driving instructions except location directions when necessary. The author secured financial resources for the commissioned drivers through a young researcher's innovation grant given by the World Conference on Transport Research Society (https://www.wctrs-society.com/wctrs-y-initiative/). The author sat in the back of the vehicle,oversaw the instruments, the coverage of the routes and recorded the start and end times and road sections covered.

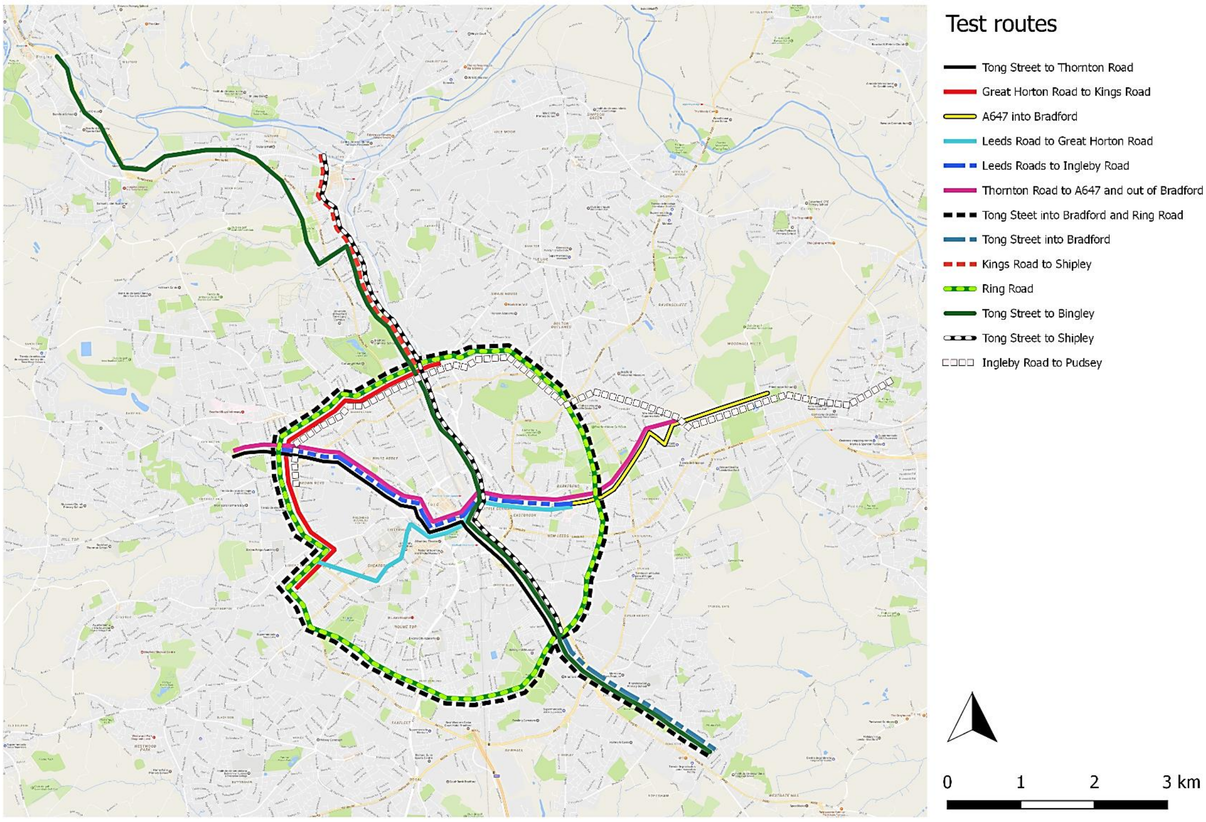


Figure 42 Test Routes surveyed in Bradford

Test routes were covered during 38 runs, which were undertaken between 24th-29th of June and 1st-28th October 2015. Over 30 hours of driving were completed covering a total distance of 650 km between the hours of 7:30 AM and 21:30 PM to account for the full range of driving and traffic conditions on the road network including AM peak, inter-peak, PM peak and off-peak conditions. The 38 runs conducted represented different roads but also the same roads in the two possible directions of travel (i.e. each direction counted as a separate run), and in different survey times (each AM peak, inter-peak, PM peak and off-peak period counted as a separate run). It was assumed that the speed profiles collected on these roads were broadly representative of driving patterns in Bradford and it is unlikely that the roads which were not surveyed differ substantially. However, some potentially important areas that were not included in the test routes due to time and resources restrictions include Halifax Road (south-west) and Great Horton Road (west-south). Further details on the vehicle tracking survey can be found in the supplementary data of Khreis et al. (2017b).

4.3.3. Data Handling and Quality Assessment

The VBOX and OBD data were time aligned manually, by matching the vehicle speed data recorded by each logger. For 11 random runs (50% of all sections with complete speed data from both loggers), speed from both loggers were compared to each other to verify them. The results of this comparison exercise demonstrated that: (a) the vehicle speed data logged by the VBOX and (b) the averaged four wheels' speed data calculated from the VBOX data matched (c) the vehicle speed data logged by the OBD, with negligible, if any, differences. For example, as shown in Figure 43, the speed data recorded by each logger had a very good level of agreement with the other and followed the same trends. This data correlated well linearly with a Pearson's correlation coefficient[3] of 0.9995.

As the measurements logged by both devices were almost identical (as shown in Figure 43), and as the RaceLogic failed in logging more often than the OBD (in 16/38 runs as compared to 4/38 runs in the final dataset), a decision was made to rely on the OBD logged data for speed values needed in the next step of instantaneous emission modelling (Section 4.3.4.). There were 4 runs where the OBD failed to log (≈ 3 hours on 29th June 2015 and ≈ 3 hours on 16th October 2015). At these incidents, the RaceLogic logged the speed data correctly and the time aligned RaceLogic speed data were used to complement missing speed data from the OBD so as not to lose this data (≈ 6 hours) from the driving cycle and subsequent emission modelling.

[3] A Pearson correlation coefficient is a measure of the linear dependence between two variables X and Y. A value of 1 implies that a linear equation describes the relationship between X and Y perfectly, with all data points lying on a line for which Y increases as X increases.

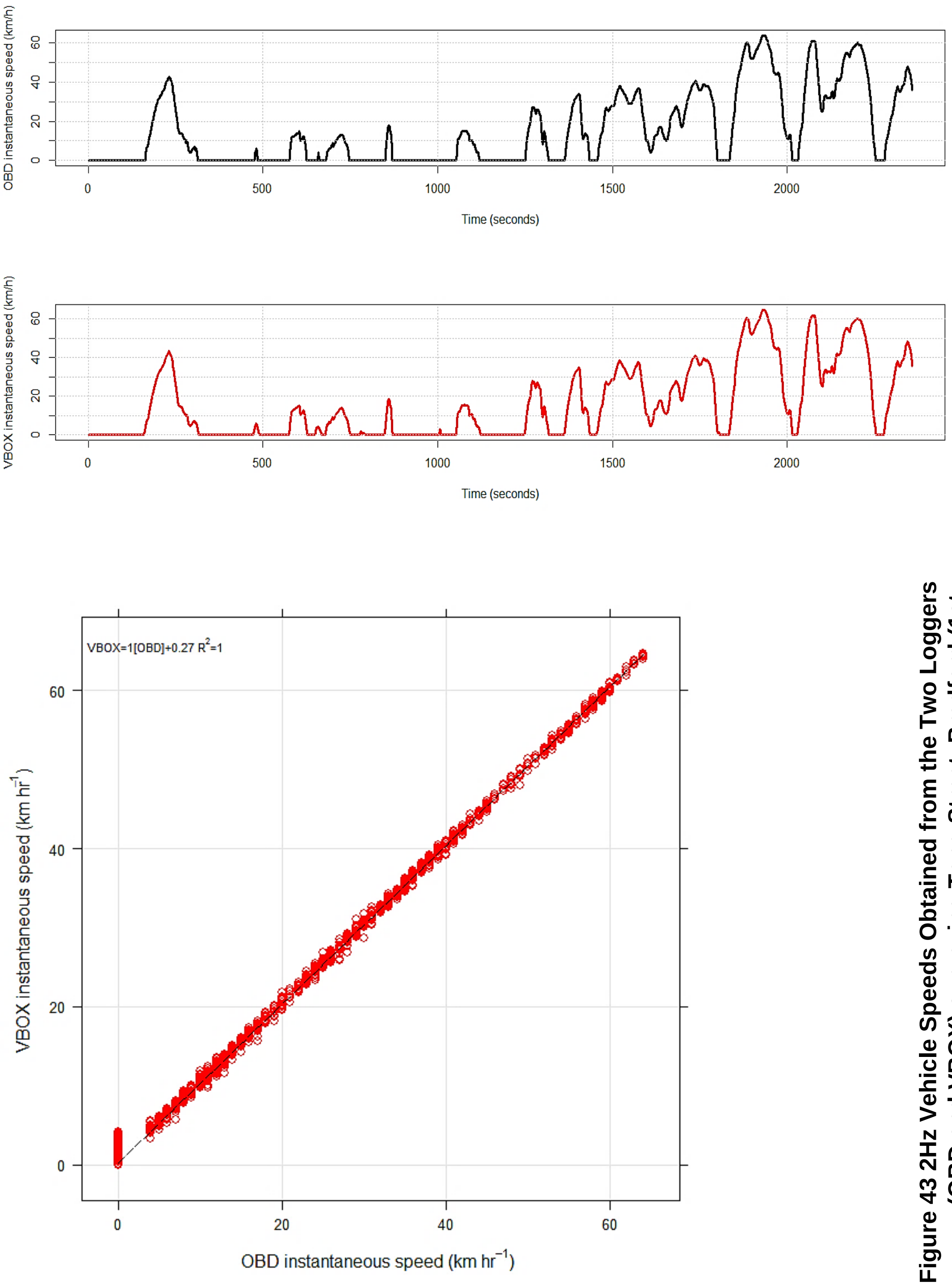


Figure 43 2Hz Vehicle Speeds Obtained from the Two Loggers (OBD and VBOX) surveying Tong Street, Bradford (1st

Simulation of Real-World Driving Cycles Emissions

4.3.4. Instantaneous Emission Modelling using PHEM

It is not feasible to comprehensively measure exhaust emissions from all vehicle classes operating in Bradford under real-world driving conditions (e.g. due to high costs and durations associated with emission measurement equipment and campaigns and the practical impossibility of recording emission levels from all current and previous vehicle classes and models on the roads). Instead, vehicle emissions were modelled using the real-world and local driving cycle trace collected in Bradford and described above.

Vehicle emissions throughout the driving trace were modelled using the power-instantaneous vehicle emission model PHEM, version 11.7.2 (Hausberger et al., 2009). PHEM is a vehicle emission model that has been recently developed by Graz University of Technology (TUG), and is one of the latest generations of vehicle emission models which exploits the relationship between engine power and exhaust emission using established engine emission maps to model second-by-second fuel consumption and exhaust emissions (Wyatt et al., 2014). The PHEM model (Figure 44) requires the following inputs: a 1 Hz vehicle speed profile (i.e. the driving cycle), road gradient (optional, alternatively road gradient can be set to zero throughout the driving cycle), and vehicle specifications data describing an average vehicle of interest including its EURO emission standard, exhaust after-treatment systems, engine size, fuel type, cross-sectional frontal area, weight, drag coefficients and transmission ratios. Once this input data is supplied, the model, based on the driving resistances and losses in the transmission systems, calculates the effective engine power and engine speed, at each second of the driving cycle, and references these values to an established average engine emission map, specific to the vehicle specification and pollutant being modelled (Boulter et al., 2007). As such, the PHEM model specifically attempts to represent the 'average' vehicle specification in a vehicle class, and not the variability of the different vehicles belonging to the same vehicle class. The key outputs of the modelling process are second-by-second estimates of fuel consumption and second-by-second emission species including carbon monoxide (CO), hydrocarbons (HC), nitrogen oxides (NO_x), nitrogen oxide (NO), particles mass (PM) and particles number (PN) (Hausberger et al., 2009). The performance and accuracy of PHEM differs across these species as overviewed in Section 4.3.5. The present work used PHEM only to model NO_x emissions as these were the most valid air quality pollutant estimates the model offers (e.g. unlike PM – Section 4.3.5.), and are emissions that could be transformed into air quality concentrations using dispersion models (e.g. unlike PN). BC, which was positively and significantly associated with asthma development (Section 2.4.5), was also not possible to model in PHEM or the dispersion model used in the next stage, and hence was excluded from this analysis.

The key difference between the PHEM and the COPERT emission models is that the former represents a complex instantaneous emission model relying on engine power and engine speed calculated from a second-by-second driving cycle to estimate EFs at a highest resolution (i.e. second-by-second). The COPERT model, on the other hand, is a simplistic average-speed-emission model assuming that EFs are a function of a vehicle's average speed, only, and providing an average-speed-emission function for each average vehicle class (Smit et al., 2010). As with the COPERT (-based) model(s), laboratory emission measurements (i.e. engine and chassis dynamometer) constitute the emission measurements database underlying the PHEM's engine emission maps. Unlike the COPERT model (Ntziachristos, 2016b), on-board real-world driving emission measurements from PEMS also constitute part of the database underlying the PHEM model (Hausberger, 2008), allowing to incorporate 'outside-of-the-laboratory' and 'off-cycle' emission measurements in the data underlying the model. PHEM also models vehicle emissions directly based on the driving cycles fed into the model. It is therefore possible, as has been done in the present work, to feed real-world and local driving cycles into the model.

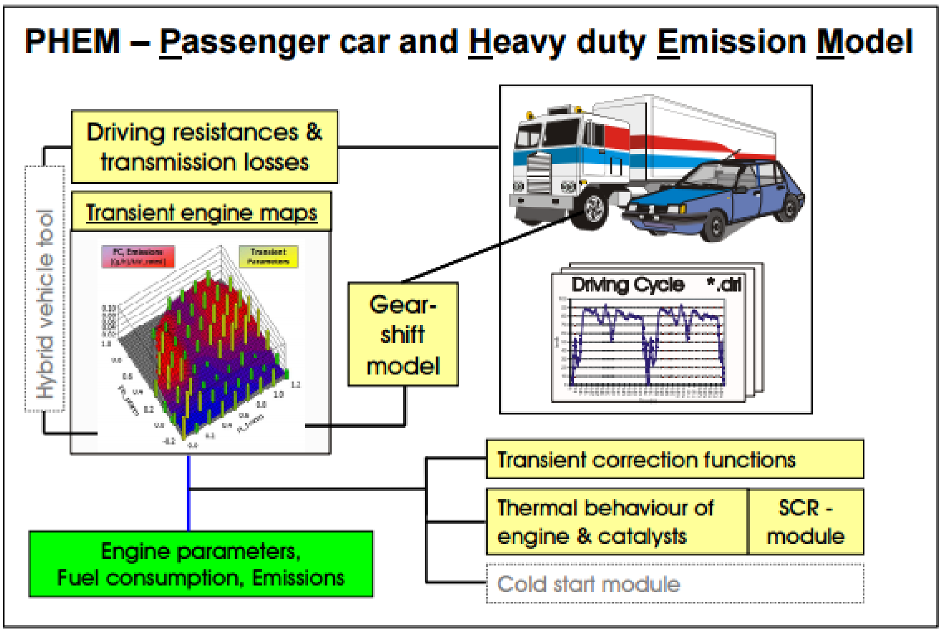


Figure 44 Scheme of the Emission Model PHEM for the Modelling of Bradford's Emission Factors, Source: Hausberger et al. (2009)

4.3.5. PHEM Validation

Testing the overall accuracy of any vehicle emission model is challenging as true vehicle emissions are unknown and are practically impossible to measure for all vehicle classes and models operating in the area and time period concerned (Smit et al., 2010). Consequently, all emission models' validation exercises, including those which will be overviewed next, are considered partial validations.

The PHEM model was validated in several studies of various vehicle samples (Hausberger et al., 2009). Boulter et al. (2007) reported that for individual HDVs, validation against measurements made on a chassis dynamometer showed that NO_x emissions estimated by PHEM were within ± 25% of the chassis dynamometer measurements. A more detailed validation exercise conducted on one articulated HDV with a kerb weight of 40 tonnes in Switzerland was described in Rexeis et al. (2005). In this study, an on-road measurement campaign was conducted measuring the vehicle's emissions and logging its driving cycle and road gradient on its travel route. For the PHEM simulations, the vehicle specifications were inputted into PHEM, alongside the logged on-road speeds and route gradients. The measured and modelled fuel consumption agreed within ± 2%, while modelled NO_x emissions were under estimated by 0%-4% (Rexeis et al., 2005). Clearly, this very replicable modelling procedure is not usually possible when deriving EFs for a larger vehicle fleet of unknown specifications and travel routes, as in the case of the present work. In another exercise undertaken to validate the average PHEM predications for passenger cars, the average emissions measured from 5 EURO 2 diesel cars operated over 12 real-world driving cycles were compared to the average emissions estimated by PHEM using specification data for an average car of the same type. The results showed a high level of accuracy for the average diesel car and the single diesel cars tested, both for fuel consumption and NO_x emissions (results only reported visually, Figure 45). The results were less accurate for other emission species including HC and PM (Boulter et al., 2007).

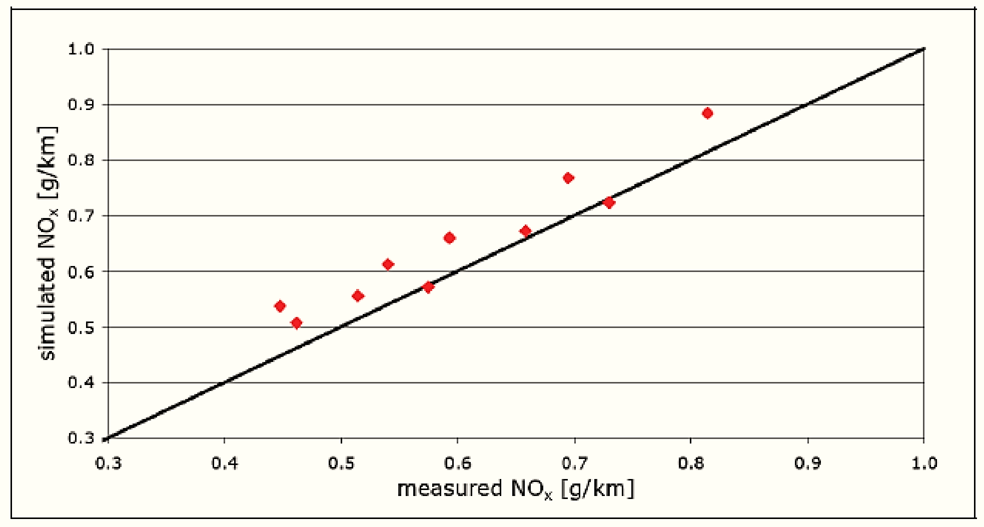


Figure 45 Simulation Quality for the Emission Factors of the Average EURO II Diesel Car in PHEM, Source: Boulter et al. (2007)

The same validation method was applied to petrol cars by testing the average EFs of 6 EURO 3 cars and comparing them with PHEM estimates of an average car of the same type. NO_x was systematically over estimated by the model (Figure 46), with the reason for this overestimation remaining unclear (Boulter et al., 2007). It is worth noting, however, that petrol passenger cars have very low absolute NO_x emissions (an order of magnitude less than the average diesel car in this example), which makes them difficult to measure and model accurately, and arguably less significant to overall emission inventories.

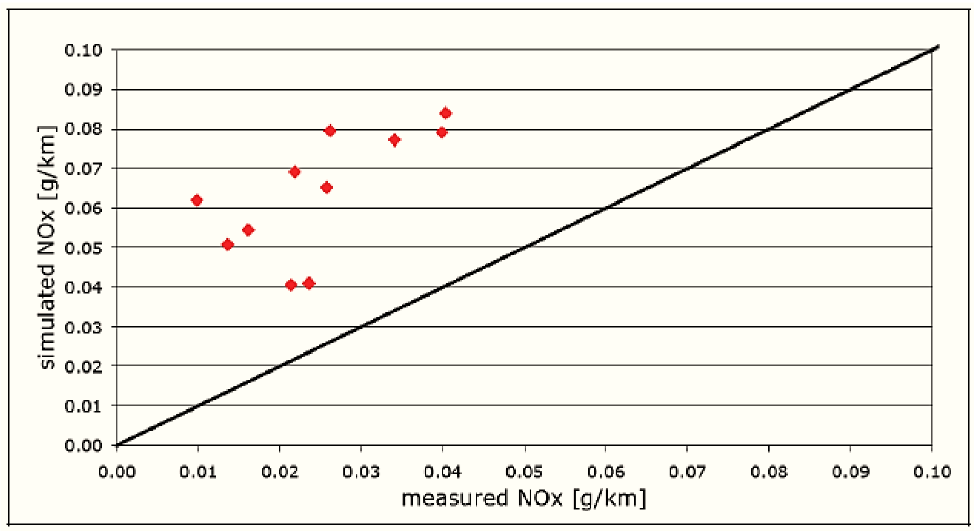


Figure 46 Simulation Quality for the Emission Factors of the Average EURO III Petrol Car in PHEM, Source: Boulter et al. (2007)

In a validation report for assessing the model, results for fuel consumption and NO_x were described to be accurate while results for PM had high uncertainty margins (Rexeis et al., 2013, Hausberger, 2008). In general, PHEM under estimated NO_x emissions at average speeds lower than 40 km/h. As for PM, modelled versus measured emissions for 10 diesel EURO 4 cars correlated poorly (results only reported visually) (Hausberger, 2008). A more recent and detailed validation exercise compared second-by-second vehicle emission measurements from a chassis dynamometer and PEMS measurements to PHEM estimates over a real-world London driving cycle developed by Transport for London (TfL) (Tate, 2015b). It was concluded that PHEM can robustly replicate the emission performance of typical vehicles but not high powered and heavier vehicles where the model's estimates were less accurate. PHEM estimates were also found more accurate for diesel vehicles than for petrol vehicles which were again emitting little NO_x making it challenging to accurately measure and model emissions. One bus was also assessed in this exercise and excellent agreement was found between measured and modelled NO_x. The differences between modelled and measured average NO_x emissions ranged from -653% to +75.5% for petrol cars; -6.5% to +36.7 for diesel cars; -42.9% to +40.2% for fully loaded HDVs and -21.2% for a Double-Decker bus (Tate, 2015b). This validation data for two diesel cars is shown next. One can, therefore, conclude that the PHEM model performs well in the estimation of NO_x emissions from typical diesel cars; HDVs and buses, although the degree of the model's accuracy depended on the vehicle being modelled and the accuracy and completion of the input data (e.g. vehicle specification data, gradient effects, engine data).

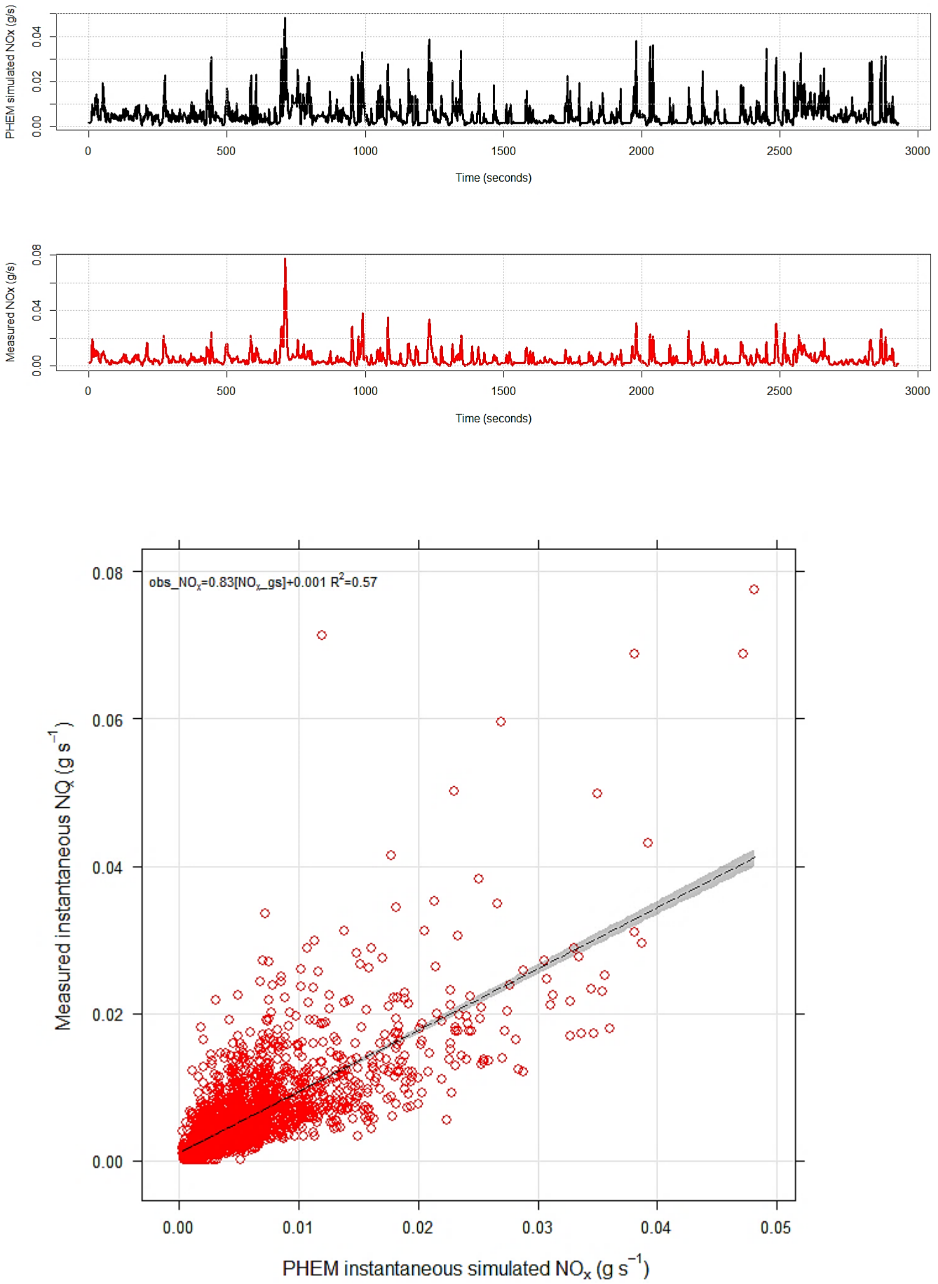


Figure 47 Second-by-Second PHEM Modelled against Measured NOx emissions (g/s), Mini/small Diesel Car, Source: Own Work (R), Data from Tate (2015b)

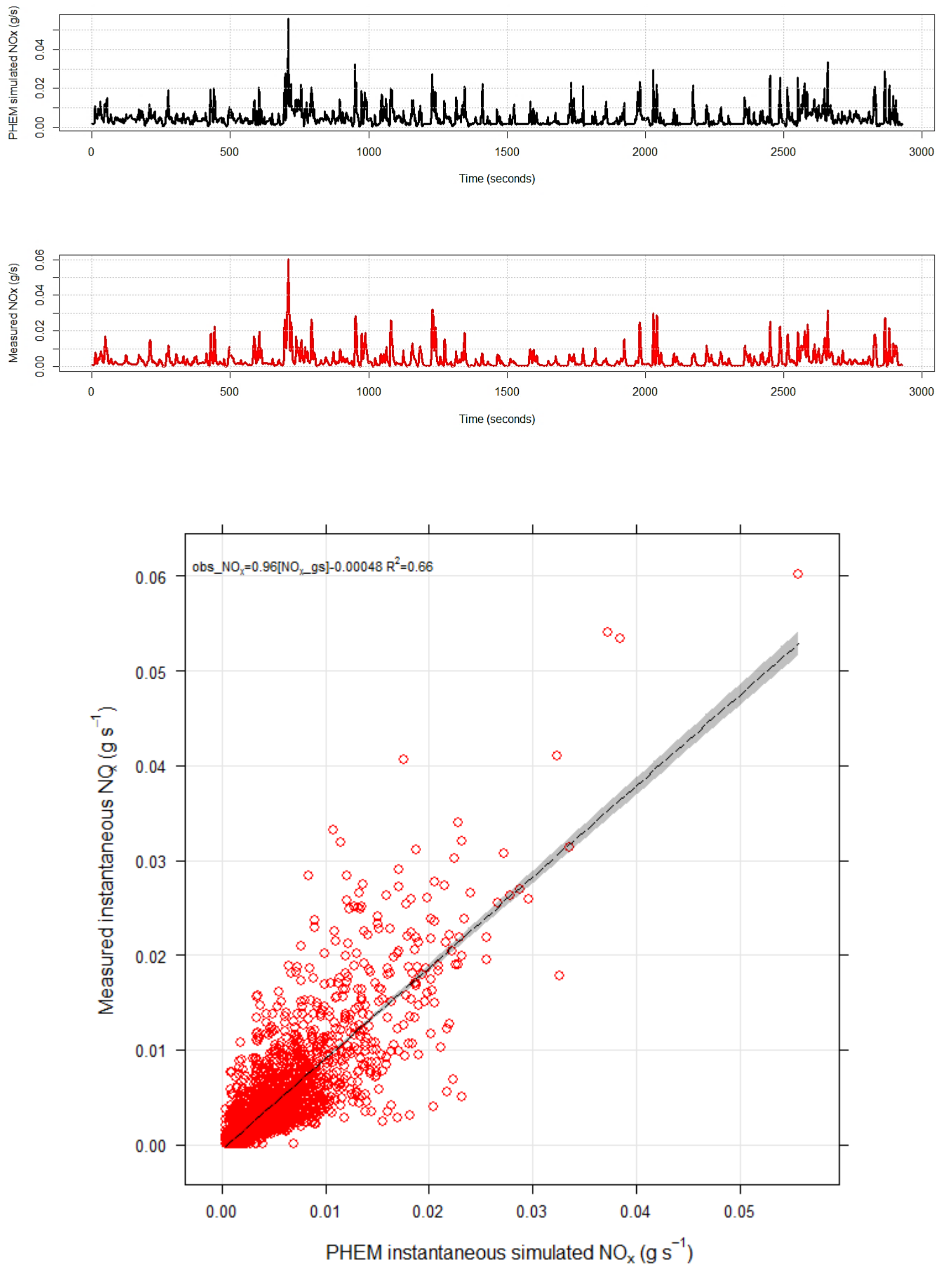


Figure 48 Second-by-Second PHEM Modelled against Measured NOx emissions (g/s), MPV/large Diesel Car, Source: Own Work (R), Data from Tate (2015b)

4.3.6. PHEM Inputs 1: Driving Cycle and Trips Definition

To meet PHEM's input requirement, the driving cycle trace collected over Bradford's test routes was converted from 2 Hz (i.e. 2 readings per second) to 1 Hz (i.e. 1 reading per second) by sampling the data and taking every other speed value recorded. This approach was preferred over averaging the two measurements made each second as averaging can smooth the transient nature of this data. The output was a second-by-second speed profile over the 30 hours of driving completed over Bradford's test routes. The second-by-second speed profile from the one tracked vehicle (see Section 4.3.1.) was assumed to apply to all other vehicles modelled. The reason was that this was the Toyota Prius was the only vehicle available for equipping and tracking at the time of the study. Further, tracking different vehicle types across the same study area's routes would have required significant time, human and monetary resources. Obviously, the tracked vehicle has different driving patterns and capabilities when compared to other vehicle classes including HDVs, buses and coaches. Nevertheless, the PHEM model ensures that the driving cycle used for a specific modelled vehicle matches the physics and capabilities of that vehicle. For example, if a HDV was being modelled using a passenger car's driving cycle (as was done in the present study), then some of the acceleration events of the passenger car would be truncated in PHEM as the HDV being modelled would not be able to achieve these levels due to its weight, air resistance etc. This is a default option within the PHEM model. In the future, it is recommended that driving cycles of different vehicle types i.e. LDVs, HGVs and Buses are surveyed, across a pool of drivers This, however, was outside the scope of this current study.

The second-by-second driving cycle trace was split into trips at which averaging the vehicle's speed and the corresponding PHEM estimated EF was undertaken. These trips were selected in a more refined and transparent manner than standard practice (Section 4.1.3.), following a 'micro-trip' approach adopted from Tate et al. (2016). A micro-trip was defined as a driving event that starts with the vehicle being stationary i.e. stop (instantaneous speed = 0 km/h) and ends with the vehicle being stationary again (instantaneous speed = 0 km/h) before it proceeds to movement in the next two seconds i.e. start (instantaneous speed = x km/h). As such, each micro-trip represented driving between adjacent stationary periods. To avoid a proliferation of very short, low-speed trip segments, the instantaneous speeds (1Hz) in all micro-trips had to equal or exceed 5 km/h. At the end of each micro-trip, the very last second of idling time (stationary) was attributed to the next micro-trip (Figure 49). A MATLAB code developed by Riley (2016) was used for splitting the driving cycle.

Splitting the driving cycle into trips between stationary periods ensures that each micro-trip includes different phases of driving including idling; acceleration; deceleration and potentially cruising. This means that no trip would be dominated by one driving phase and that emissions from the acceleration and deceleration phases can be balanced thereby reducing the scatter of the average-speed-emissions data and making subsequent function fitting more reasonable than is being done for the COPERT model (e.g. Figure 37). Finally, using this approach means that averaging EFs is undertaken at the longer links for higher average speeds and vice versa. This naturally matches the nature of the traffic network data where longer links are usually motorway links with higher speeds and cruising proportions while shorter links are usually urban links and road sections between junctions, crossings and turns in urban areas with lower speeds and higher stop-start driving proportions.

The Bradford driving cycle was split into 1390 micro-trips. The micro-trips were given separate IDs and the splitting was undertaken separately at each day so as not to mix the idling duration at the end of one day with the idling duration at the start of another. The shortest micro-trip recorded in time was 3 seconds, which related to 3 seconds of zero, 5 and 0 km/h instantaneous speeds before the vehicle cruised again. The longest micro-trip recorded in time was 919 seconds (≈ 15 minutes), which related to continuous driving over a stretch of ≈ 3.6 km and at an average speed of ≈ 14.1 km/h. In distance, the recorded micro-trips covered a distance ranging from 1.389 m to 12694 m and had an average speed ranging from 0.2857 km/h to 78.9278 km/h, as shown in Table 15.

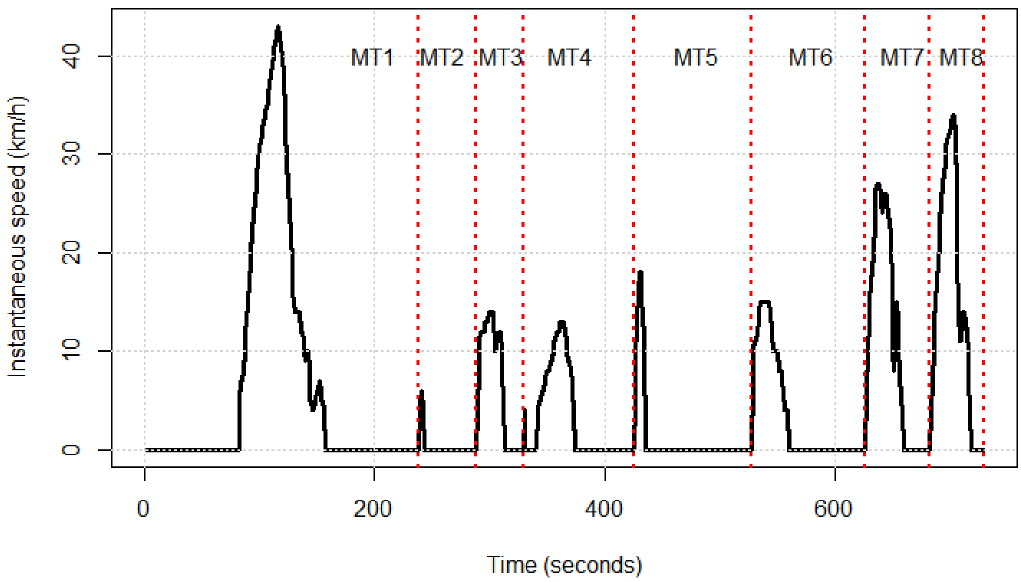


Figure 49 Illustrative Time Series with Micro-Trip (MT) Start Points Annotated in Red Dashed Lines, Source: Own Work (R)

Table 15 Micro-trip Summary Statistics (N=1390 micro-trips)

Statistic	Micro-trip distance (km)	Micro-trip time (s)	Micro-trip average speed (km/h)
Minimum	0.001389	3.00	0.2857
1st quartile	0.034583	29.00	4.3604
Median	0.157222	59.00	11.7600
Mean	0.467699	77.95	15.0534
3rd quartile	0.590556	98.00	24.6097
Maximum	12.694220	919.00	78.9278

4.3.7. PHEM Inputs 2: Vehicle Specifications

In addition to the second-by-second driving cycle trace, PHEM requires specifications data for the vehicles whose emissions will be modelled. To enable a meaningful comparison with the standard average-speed-emission functions used in the UK, the COPERT 4 v10.0 average-speed-emission functions given in the UK emission factor toolkit v6.0 were visited and the same vehicle classes that were considered in this toolkit were selected for the PHEM modelling. Traffic data splits in the UK are also given based on these vehicle classes, which reinforces this selection and makes it consistent with the latest fleet composition projections and methods used in the NAEI. The vehicles types and specifications that have average-speed-emission functions in the UK emission factor toolkit can be found in the COPERT 4 v10.0 spreadsheet, which at the time of this work was the final version published in November 2012. This is freely available from http://naei.defra.gov.uk/data/ef-transport and includes the vehicles classes/specifications listed in Table 16. Bendy buses > 18 tonnes were excluded from this list, as they do not operate in Bradford. LDVs were also modelled in 3 separate weight categories instead of 1 as practiced in COPERT, to better represent the effect of weight on these vehicles' emissions.

In total, 167 individual vehicles were modelled in PHEM and this data was subsequently used to derive average-speed-emission functions for each vehicle class, technology and fuel. The exact vehicle specifications used for each vehicle modelled including its kerb weight, load, frontal area and engine power are given in supplementary data of Khreis et al. (2017b). These specifications were based on vehicle specifications observed in an automatic number plate recognition survey in Leeds, UK, which covered 14,574 passenger cars and light duty vehicles (Wyatt et al., 2016) and in London, UK, for heavy duty vehicles, buses and coaches where there was a bigger sample (4,852 compared to 1,263 observed in Leeds) that was considered more appropriate for averaging specifications across the numerous HDV, buses and coaches categories modelled (Tate et al., 2016). No equivalent data was available for Bradford.

Table 16 Vehicle Classes Modelled in PHEM (N=167)

Vehicle class	Weight class	EURO emission standard
Diesel passenger cars	NA	(6 EURO standards) Pre-EURO – EURO 5
Petrol passenger cars	NA	(6 EURO standards) Pre-EURO – EURO 5
Diesel light duty vehicles	Class I	(6 EURO standards) Pre-EURO – EURO 5
Diesel light duty vehicles	Class II	(6 EURO standards) Pre-EURO – EURO 5
Diesel light duty vehicles	Class III	(6 EURO standards) Pre-EURO – EURO 5
Petrol light duty vehicles	Class I	(6 EURO standards) Pre-EURO – EURO 5
Petrol light duty vehicles	Class II	(6 EURO standards) Pre-EURO – EURO 5
Petrol light duty vehicles	Class III	(6 EURO standards) Pre-EURO – EURO 5
Diesel buses	≤ 15 tonnes (single-decker)	(7 EURO standards) Pre-EURO – EURO 5 (EURO 5 split into EGR and SCR technology)
Diesel buses	15-18 tonnes (double-decker)	(7 EURO standards) Pre-EURO – EURO 5 (EURO 5 split into EGR and SCR technology)
Diesel coaches	≤ 18 tonnes (small)	(7 EURO standards) Pre-EURO – EURO 5 (EURO 5 split into EGR and SCR technology)
Diesel coaches	> 18 tonnes (large)	(7 EURO standards) Pre-EURO – EURO 5 (EURO 5 split into EGR and SCR technology)
Diesel rigid heavy duty vehicles	≤ 7.5 tonnes	(7 EURO standards) Pre-EURO – EURO 5 (EURO 5 split into EGR and SCR technology)
Diesel rigid heavy duty vehicles	7.5-12 tonnes	(7 EURO standards) Pre-EURO – EURO 5 (EURO 5 split into EGR and SCR technology)
Diesel rigid heavy duty vehicles	12-14 tonnes	(7 EURO standards) Pre-EURO – EURO 5 (EURO 5 split into EGR and SCR technology)
Diesel rigid heavy duty vehicles	14-20 tonnes	(7 EURO standards) Pre-EURO – EURO 5 (EURO 5 split into EGR and SCR technology)
Diesel rigid heavy duty vehicles	20-26 tonnes	(7 EURO standards) Pre-EURO – EURO 5 (EURO 5 split into EGR and SCR technology)
Diesel rigid heavy duty vehicles	26-28 tonnes	(7 EURO standards) Pre-EURO – EURO 5 (EURO 5 split into EGR and SCR technology)
Diesel rigid heavy duty vehicles	28-32 tonnes	(7 EURO standards) Pre-EURO – EURO 5 (EURO 5 split into EGR and SCR technology)
Diesel rigid heavy duty vehicles	> 32 tonnes	(7 EURO standards) Pre-EURO – EURO 5 (EURO 5 split into EGR and SCR technology)
Diesel articulated heavy duty vehicles	14-20 tonnes	(7 EURO standards) Pre-EURO – EURO 5 (EURO 5 split into EGR and SCR technology)
Diesel articulated heavy duty vehicles	20-28 tonnes	(7 EURO standards) Pre-EURO – EURO 5 (EURO 5 split into EGR and SCR technology)
Diesel articulated heavy duty vehicles	28-34 tonnes	(7 EURO standards) Pre-EURO – EURO 5 (EURO 5 split into EGR and SCR technology)

Diesel articulated heavy duty vehicles	34-40 tonnes	(7 EURO standards) Pre-EURO – EURO 5 (EURO 5 split into EGR and SCR technology)
Articulated heavy duty vehicles	40-50 tonnes	(7 EURO standards) Pre-EURO – EURO 5 (EURO 5 split into EGR and SCR technology)

4.3.8. Average-Speed-Emission Functions Development

All analysis and average-speed-emission function development/fitting was undertaken in the open source software R (R Core Team, 2013), namely Rstudio version 3.2.2. For each modelled vehicle class, technology and fuel, the outputs from PHEM were second-by-second emission estimates (g/h), averaged over each micro-trip as defined in Section 4.3.6. Each micro-trip was given a unique ID, and the average emission estimate (g/h), and the average speed (km/h) for the micro-trip were extracted. To develop average-speed-emission functions from this data, the modelled average NO_x in g/h (raw PHEM output) was converted to g/km (i.e. distance based EF) using the average micro-trip speed.

At each micro-trip, the average-speed and its corresponding average-emission factor calculated from PHEM results as above yielded one data point (x: average micro-trip speed (km/h), y: average NO_x EF (g/km)). For each modelled vehicle class, technology and fuel, all the resulting x-y data points were plotted and used as the underlying data to fit a new average-speed-emission function for each vehicle. The relation between the average micro-trip speed and the average NO_x EF at the micro-trip level was captured by fitting a linear logarithmic regression function between the two using the R-project 'lm' function (https://stat.ethz.ch/R-manual/R-devel/library/stats/html/lm.html). All average-speed-emissions functions were developed by the author to a common logarithmic expression of the form:

$$\mathrm{Log}\left(\mathrm{NOx}\,(\frac{\mathrm{g}}{\mathrm{km}})\right) = \mathrm{Intercept} + \mathrm{Estimate} * \mathrm{Log}\,(\mathrm{Average\ micro-trip\ speed}\left(\frac{\mathrm{km}}{\mathrm{h}}\right)) \ldots (\mathrm{Equation\ 4.5.})$$

All logs are natural logs of the base e. This process was repeated 167 times to fit average-speed-emission functions to all the vehicle classes, technologies and fuels modelled in PHEM. For each fitted average-speed-emission function, a summary of the 'lm' function's output was produced and saved as a .txt file. In this summary, statistics on the following parameters were given: the intercept alongside its standard error and significance level; the log (speed_km/h) estimate alongside its standard error and significance level; the residual standard error; the multiple and adjusted R squared. These are documented in Table 18 to give an indication of the performance of the fitted functions. As an example, Figure 50 illustrates the underlying data points and the fitted average-speed-emission function for a diesel EURO 4 passenger car, the most common passenger car sub-category in 2009.

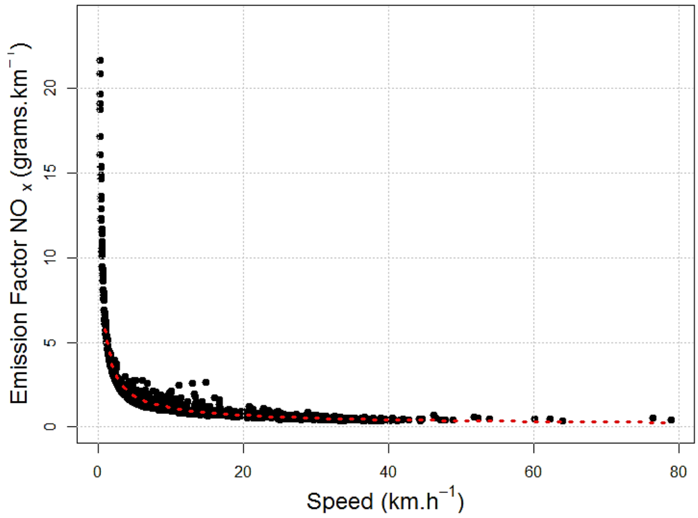


Figure 50 Underlying Data Points and Fitted Average-Speed-Emission Function for a Diesel EURO 4 Passenger Car, Source: Own Work (R)

4.3.9. Comparison with the COPERT Functions

All standard average-speed-emission functions were sourced from the COPERT 4 v10.0 spreadsheet, which at the time of this work was the latest version published in November 2012. This is freely available and was accessed from http://naei.defra.gov.uk/data/ef-transport. Using this spreadsheet, the average-speed-emission functions given were extracted onto a new Excel spreadsheet and were manually parameterized per the vehicle's type, technology and fuel. These functions offered a reference point for comparing the performance of the new versus the standard average-speed-emission functions.

As the COPERT functions were not designed to be used at very low average speeds (<5-12 km/h; depending on the vehicle type), the COPERT spreadsheets provide minimum speed limits (km/h) for the functions to be used reasonably. These differ by vehicle class and range from 5 km/h (for petrol passenger cars) to 12 km/h (for HDVs, buses and coaches). In practice, when the average speed entered/specified is below the minimum speed allowed for that vehicle class's average-speed-emission function, the minimum is assumed (Department for Environment Food and Rural Affairs, 2014b). This standard procedure was followed when applying the COPERT functions in this work.

The new PHEM-based average-speed-emission functions were developed for the same vehicle classes given in COPERT 4 v10.0 except in the case LDV as mentioned in Section 4.3.7. In COPERT, there is only a single given set of LDVs average-speed-emission functions and it is recommended that this should be used for the two weight classes of LDVs (class II and class III). For small LDVs (class I) with car body types, the sheet recommends using average-speed-emission functions for medium-sized cars. In this work, the 3 weight categories of LDVs were separately modelled in PHEM and those were compared to average-speed-emission functions from COPERT following its recommendation (i.e. PHEM class I LDVs was compared to COPERT medium-sized cars and PHEM class II and III LDVs were compared to COPERT LDVs single set of functions).

Both, new and standard, average-speed-emission functions were coded onto an Excel spreadsheet so that the user only needs to enter the average vehicle speed on each spreadsheet for the NO_x EFs to be calculated. The spreadsheet provides separate NO_x EFs for EURO V buses, coaches and HDVs with Selective Catalytic Reduction (SCR) and Exhaust Gas Recirculation (EGR) systems. Neither standard (COPERT) nor new (PHEM-based) functions were corrected for accumulated mileage/age, which causes further emission degradation, as this data was not available. Neither functions were corrected for fuel quality (applicable in the case of petrol only), as this data was not available.

4.4. Results

4.4.1. Driving Cycle Summary Statistics

A total of 30.5 hours of driving (or 109,817 instantaneous speed records) were completed over Bradford’s road network, capturing multiple AM peak, inter-peak, PM peak and off-peak periods and driving conditions. The average vehicle speed without stops was 30.87 km/h. Table 17 is a comparison between the key variables from the real-world Bradford’s driving cycle and the two European type approval test cycle: the current NEDC and the proposed Worldwide harmonized Light Vehicles Test Procedures (WLTP). The table demonstrates that the key differences between the real-world driving cycle collated in this study and the two regulatory cycles are the percentage of idling, which is higher in real-world driving and the percentage of cruising, which is lower in real-world driving when compared to the NEDC.

The average speeds, with and without stops, in real-world driving were lower than both type approval regulatory cycles. No speed above 110 km/h was recorded in the real-world driving cycle in Bradford, partly because of the limited nature of the roads surveyed including inner city roads, single and dual carriageways but largely missing motorways. The lowest and highest accelerations recorded during the real-world driving cycle were significantly higher than both type approval regulatory cycles, suggesting that regulatory cycles do not achieve the same levels of abruptness in acceleration and deceleration feasible in real-world driving. The percentages of acceleration and deceleration time were higher in Bradford when compared to the NEDC, while the opposite is true when compared to WLTP. Real-world driving in this study spent the clear majority of time at speeds < 40 km/h and only 17% and 2% of the time at speeds between 40-60 km/h and higher than 60 km/h, respectively.

Table 17 Driving Cycle Parameters

Driving cycle	NEDC	WLTP class 3*	Bradford real-world
Duration (seconds)	1220 (≈20.3 minutes)	1800 (30 minutes)	109817 (1830 minutes ≈30.5 hours)
Distance (kilometre)	11.00	23.13	650.76
% idling** time (%)	26.31	12.61	29.57
% cruising*** time (%)	40.98	0.84	20.08
Average speeds with stops (km/h)	32.47	46.26	21.33
Average speeds without stops (km/h)	44.70	53.20	30.87
Maximum speed (km/h)	120	131	110
Average (positive) acceleration**** (m/s^2)	0.59	0.41	0.58
Maximum acceleration (m/s^2)	1.06	1.88	4.72
Average (negative) deceleration***** (m/s^2)	-0.75	-0.43	-0.66
Maximum deceleration (m/s^2)	-1.39	-1.52	-6.67
% acceleration time	20.25	44.06	26.78
% deceleration time	12.46	42.5	23.57
% time spent at 0-40 km/h	65.41	48.72	80.34
% time spent at >40-60 km/h	15.57	19.39	17.27
% time spent at > 60 km/h	19.10	31.94	2.39

* *class 3 cycle total (highest power-to-mass ratio, representative of vehicles driven in Europe and Japan)*

** *The idle mode is defined as zero speed and zero acceleration*

*** *Cruising defined as all other driving besides idling, accelerating and decelerating*

**** *Acceleration > 0 m/s^2*

***** *Deceleration < 0 m/s*

4.4.2. New Average-Speed-Emission Functions

In total, 164 new average-speed-emission functions were developed to a common logarithmic expression (Equation 4.5) for the full fleet of diesel and petrol passenger cars and LDVs, diesel buses, coaches, rigid and articulated HDVs in Bradford. It was not possible to fit an acceptable function to the pre-EURO petrol LDVs PHEM data (class I, II and III) due to the high degree of scatter which was not possible to capture through an acceptable fitted model (R^2 fitted = 0.0002 for petrol LDV class I, 0.0025 for class II, 0.0002 for class III). The standard COPERT functions will be used for these three vehicles in the final analysis. All logarithms were natural logarithms (a logarithm to the base *e*). Each fitted function represents the relation between a specific vehicle's average speed in km/h (the predictor variable), and its NO_x EF in g/km (the response variable). These functions are given in Table 18, alongside a measure of the goodness of fit (adjusted R-squared), the errors associated with each coefficient and its significance level. The functions were coded onto an Excel spreadsheet as shown in Equation 4.6.

$$\mathrm{NOx}\,(\frac{\mathrm{g}}{\mathrm{km}}) = \mathrm{EXP}((\mathrm{Intercept}) + (\mathrm{Estimate} * \mathrm{LN}(\mathrm{Average\ speed}\left(\frac{\mathrm{km}}{\mathrm{h}}\right)) \ldots (\mathrm{Equation\ 4.6.})$$

The Excel spreadsheet is being made open access and the user only needs to enter the average vehicle speed (km/h) at each link to calculate the NO_x EF (g/km) for each vehicle class. The functions were developed and coded for the emission standards pre-EURO (EURO 0) to EURO 5/V, which were the vehicle emission standards in operation in Bradford in the investigation year: 2009. The following model parameters were produced and examined to give an indication of the fitted model/function's quality: the adjusted R-squared, the residual standard error of the model, the standard error of the coefficients of the model, and their significance level (Table 18).

The adjusted R-squared provides a measure of how well the model can explain the variance of the response variable, while adjusting for the number of variables considered. An R^2 value of ≥ 0.7 (70%) was considered a good model fit. The residual standard error is the average amount the response variable will deviate from the true regression line. The smaller this value is, the better. This value is presented to be able to compare it across the different vehicle classes. The coefficient standard error is a measure of the average difference the coefficient estimates vary from the average value of the response variable. This needs to be a low number relative to its corresponding coefficient. The coefficient standard error is ideally an order of magnitude less than the coefficient estimate. The p value (significance level) indicates the likelihood to observe a relationship between the predictor and response variables due to chance. Typically, a p-value of 5% or less is a good cut-off point. Three stars (or asterisks) represent a highly significant p-value, which allows concluding that it's unlikely that no relationship exists between the average micro-trip speed and NO_x EF. The cases where the fitted model/function's quality was more uncertain were underlined in red in Table 18. These cases were very few (9 out of 164) and included: petrol passenger cars pre-EURO (R^2=0.60), EURO 1 (R^2=0.54), EURO 2 (intercept's standard error not less than an order of magnitude than the coefficient estimate), and petrol LDVs (class I, II and III) EURO 1 and EURO 2, where R^2 was < 0.7. In these cases, there was a high degree of scatter in the underlying data.

Table 18 Newly Developed PHEM-based NO_x Average-Speed-Emission Functions for Diesel and Petrol Passenger Cars and Light Duty Vehicles, Diesel Buses, Coaches and Articulated and Rigid Heavy Duty Vehicles

Diesel Passenger Cars							
EURO emission standard	Average-speed-emission function (PHEM-based)	Residual standard error	Adjusted R-squared (R^2)	Intercept (standard error)	Intercept variable p-value	Log average speed coefficient (standard error)	Log average speed variable p-value
EURO 0	Log (NO_x g/km) = 1.804367 - 0.715172 * log (average speed km/h)	0.1399	0.97	1.804367 (0.008434)	<2e-16 ***	- 0.715172 (0.003363)	<2e-16 ***
EURO 1	Log (NO_x g/km) = 1.530742 - 0.616698 * log (average speed km/h)	0.1630	0.95	1.530742 (0.009826)	<2e-16 ***	- 0.616698 (0.003918)	<2e-16 ***
EURO 2	Log (NO_x g/km) = 1.689483 - 0.624366 * log (average speed km/h)	0.1605	0.95	1.689483 (0.009679)	<2e-16 ***	- 0.624366 (0.003859)	<2e-16 ***
EURO 3	Log (NO_x g/km) = 1.342277 - 0.540600 * log (average speed km/h)	0.2165	0.89	1.342277 (0.013054)	<2e-16 ***	- 0.540600 (0.005205)	<2e-16 ***
EURO 4	Log (NO_x g/km) = 1.751140 - 0.705770 * log (average speed km/h)	0.1714	0.96	1.75114 (0.01033)	<2e-16 ***	- 0.70577 (0.00412)	<2e-16 ***
EURO 5	Log (NO_x g/km) = 1.282085 - 0.523087 * log (average speed km/h)	0.1750	0.92	1.282085 (0.010552)	<2e-16 ***	- 0.523087 (0.004207)	<2e-16 ***
Petrol Passenger Cars							
EURO emission standard	Average-speed-emission function (PHEM-based)	Residual standard error	Adjusted R-squared (R^2)	Intercept (standard error)	Intercept variable p-value	Log average speed coefficient (standard error)	Log average speed variable p-value
EURO 0	Log (NO_x g/km) = 0.323756 - 0.276685 * log (average speed km/h)	0.2538	0.60	0.323756 (0.015301)	<2e-16 ***	- 0.276685 (0.006101)	<2e-16 ***
EURO 1	Log (NO_x g/km) = - 0.198028 - 0.263900 * log (average speed km/h)	0.2744	0.54	- 0.198028 (0.016544)	<2e-16 ***	- 0.263900 (0.006597)	<2e-16 ***
EURO 2	Log (NO_x g/km) = 0.085971 - 0.446916 * log (average speed km/h)	0.1899	0.87	0.085971 (0.011446)	<2e-16 ***	- 0.446916 (0.004564)	<2e-16 ***
EURO 3	Log (NO_x g/km) = - 1.074521 - 0.445470 * log (average speed km/h)	0.1910	0.87	- 1.074521 (0.011517)	<2e-16 ***	- 0.445470 (0.004592)	<2e-16 ***
EURO 4	Log (NO_x g/km) = - 1.442175 - 0.440882 * log (average speed km/h)	0.1999	0.86	- 1.442175 (0.012050)	<2e-16 ***	- 0.440882 (0.004804)	<2e-16 ***
EURO 5	Log (NO_x g/km) = - 2.183611 - 0.352004 * log (average speed km/h)	0.1756	0.83	- 2.183611 (0.010589)	<2e-16 ***	- 0.352004 (0.004222)	<2e-16 ***
Diesel Light Duty Vehicles – Weight Class I							
EURO emission standard	Average-speed-emission function (PHEM-based)	Residual standard error	Adjusted R-squared (R^2)	Intercept (standard error)	Intercept variable p-value	Log average speed coefficient (standard error)	Log average speed variable p-value
EURO 0	Log (NO_x g/km) = 1.892855 - 0.571284 * log (average speed km/h)	0.1817	0.93	1.892855 (0.010953)	<2e-16 ***	- 0.571284 (0.004367)	<2e-16 ***
EURO 1	Log (NO_x g/km) = 1.706481 - 0.566210 * log (average speed km/h)	0.1841	0.92	1.706481 (0.011096)	<2e-16 ***	- 0.566210 (0.004424)	<2e-16 ***
EURO 2	Log (NO_x g/km) = 1.598613 - 0.569017 * log (average speed km/h)	0.1799	0.93	1.598613 (0.010849)	<2e-16 ***	- 0.569017 (0.004325)	<2e-16 ***
EURO 3	Log (NO_x g/km) = 0.955508 - 0.494470 * log (average speed km/h)	0.2121	0.87	0.955508 (0.012786)	<2e-16 ***	- 0.494470 (0.005098)	<2e-16 ***
EURO 4	Log (NO_x g/km) = 1.259996 - 0.568199 * log (average speed km/h)	0.2336	0.88	1.259996 (0.014080)	<2e-16 ***	- 0.568199 (0.005614)	<2e-16 ***
EURO 5	Log (NO_x g/km) = 1.266065 - 0.618294 * log (average speed km/h)	0.2177	0.91	1.266065 (0.013122)	<2e-16 ***	- 0.618294 (0.005232)	<2e-16 ***
Diesel Light Duty Vehicles – Weight Class II							
EURO emission standard	Average-speed-emission function (PHEM-based)	Residual standard error	Adjusted R-squared (R^2)	Intercept (standard error)	Intercept variable p-value	Log average speed coefficient (standard error)	Log average speed variable p-value
EURO 0	Log (NO_x g/km) = 1.946052 - 0.546533 * log (average speed km/h)	0.1916	0.91	1.946052 (0.011552)	<2e-16 ***	- 0.546533 (0.004606)	<2e-16 ***
EURO 1	Log (NO_x g/km) = 1.846413 - 0.560846 * log (average speed km/h)	0.1856	0.92	1.846413 (0.011191)	<2e-16 ***	- 0.560846 (0.004462)	<2e-16 ***
EURO 2	Log (NO_x g/km) = 1.739964 - 0.559784 * log (average speed km/h)	0.1812	0.92	1.739964 (0.010924)	<2e-16 ***	- 0.559784 (0.004356)	<2e-16 ***
EURO 3	Log (NO_x g/km) = 1.262472 - 0.505039 * log (average speed km/h)	0.209	0.88	1.262472 (0.012598)	<2e-16 ***	- 0.505039 (0.005023)	<2e-16 ***
EURO 4	Log (NO_x g/km) = 1.090972 - 0.532336 * log (average speed km/h)	0.244	0.86	1.090972 (0.014731)	<2e-16 ***	- 0.532336 (0.005873)	<2e-16 ***
EURO 5	Log (NO_x g/km) = 1.073345 - 0.556929 * log (average speed km/h)	0.2361	0.87	1.073345 (0.014234)	<2e-16 ***	- 0.556929 (0.005675)	<2e-16 ***

Diesel Light Duty Vehicles – Weight Class III							
EURO emission standard	Average-speed-emission function (PHEM-based)	Residual standard error	Adjusted R-squared (R^2)	Intercept (standard error)	Intercept variable p-value	Log average speed coefficient (standard error)	Log average speed variable p-value
EURO 0	Log (NO_x g/km) = 1.846234 - 0.496097 * log (average speed km/h)	0.2099	0.87	1.846234 (0.012654)	<2e-16 ***	- 0.496097 (0.005046)	<2e-16 ***
EURO 1	Log (NO_x g/km) = 1.80597 - 0.51088 * log (average speed km/h)	0.2055	0.89	1.80597 (0.01239)	<2e-16 ***	- 0.51088 (0.00494)	<2e-16 ***
EURO 2	Log (NO_x g/km) = 1.772454 - 0.532798 * log (average speed km/h)	0.1939	0.90	1.772454 (0.011689)	<2e-16 ***	- 0.532798 (0.004661)	<2e-16 ***
EURO 3	Log (NO_x g/km) = 1.515181 - 0.473228 * log (average speed km/h)	0.2221	0.85	1.515181 (0.013389)	<2e-16 ***	- 0.473228 (0.005339)	<2e-16 ***
EURO 4	Log (NO_x g/km) = 1.313255 - 0.555176 * log (average speed km/h)	0.2373	0.87	1.313255 (0.014308)	<2e-16 ***	- 0.555176 (0.005705)	<2e-16 ***
EURO 5	Log (NO_x g/km) = 1.305634 - 0.573082 * log (average speed km/h)	0.2299	0.89	1.305634 (0.013857)	<2e-16 ***	- 0.573082 (0.005525)	<2e-16 ***
Petrol Light Duty Vehicles – Weight Class I							
EURO emission standard	Average-speed-emission function (PHEM-based)	Residual standard error	Adjusted R-squared (R^2)	Intercept (standard error)	Intercept variable p-value	Log average speed coefficient (standard error)	Log average speed variable p-value
EURO 0	Underlying data did not allow a new function fitting – standard COPRT function will be used in the final analysis						
EURO 1	Log (NO_x g/km) = 0.784251 - 0.333349 * log (average speed km/h)	0.3036	0.60	0.784251 (0.018304)	<2e-16 ***	- 0.333349 (0.007299)	<2e-16 ***
EURO 2	Log (NO_x g/km) = - 0.229573 - 0.332977 * log (average speed km/h)	0.3026	0.60	- 0.229573 (0.018244)	<2e-16 ***	- 0.332977 (0.007275)	<2e-16 ***
EURO 3	Log (NO_x g/km) = - 0.826689 - 0.460544 * log (average speed km/h)	0.2396	0.82	- 0.826689 (0.014447)	<2e-16 ***	- 0.460544 (0.005761)	<2e-16 ***
EURO 4	Log (NO_x g/km) = - 1.845076 - 0.323903 * log (average speed km/h)	0.2338	0.71	- 1.845076 (0.014093)	<2e-16 ***	- 0.323903 (0.005619)	<2e-16 ***
EURO 5	Log (NO_x g/km) = - 2.864948 - 0.325814 * log (average speed km/h)	0.2338	0.71	- 2.864948 (0.014097)	<2e-16 ***	- 0.325814 (0.005621)	<2e-16 ***
Petrol Light Duty Vehicles – Weight Class II							
EURO emission standard	Average-speed-emission function (PHEM-based)	Residual standard error	Adjusted R-squared (R^2)	Intercept (standard error)	Intercept variable p-value	Log average speed coefficient (standard error)	Log average speed variable p-value
EURO 0	Underlying data did not allow a function fitting – standard COPRT function will be used in the final analysis						
EURO 1	Log (NO_x g/km) = 1.116269 - 0.335839 * log (average speed km/h)	0.3027	0.61	1.116269 (0.018249)	<2e-16 ***	- 0.335839 (0.007277)	<2e-16 ***
EURO 2	Log (NO_x g/km) = 0.054921 - 0.340592 * log (average speed km/h)	0.3023	0.61	0.054921 (0.018222)	0.00262 **	- 0.340592 (0.007266)	< 2e-16 ***
EURO 3	Log (NO_x g/km) = - 0.502884 - 0.468269 * log (average speed km/h)	0.2349	0.83	- 0.502884 (0.014163)	<2e-16 ***	- 0.468269 (0.005647)	<2e-16 ***
EURO 4	Log (NO_x g/km) = - 1.679280 - 0.331347 * log (average speed km/h)	0.2339	0.71	- 1.679280 (0.014099)	<2e-16 ***	- 0.331347 (0.005622)	<2e-16 ***
EURO 5	Log (NO_x g/km) = - 2.699937 - 0.332527 * log (average speed km/h)	0.2338	0.72	- 2.699937 (0.014093)	<2e-16 ***	- 0.332527 (0.005619)	<2e-16 ***
Petrol Light Duty Vehicles – Weight Class III							
EURO emission standard	Average-speed-emission function (PHEM-based)	Residual standard error	Adjusted R-squared (R^2)	Intercept (standard error)	Intercept variable p-value	Log average speed coefficient (standard error)	Log average speed variable p-value
EURO 0	Underlying data did not allow a function fitting – standard COPRT function will be used in the final analysis						
EURO 1	Log (NO_x g/km) = 1.316897 - 0.334037 * log (average speed km/h)	0.3043	0.60	1.316897(0.018344)	<2e-16 ***	- 0.334037 (0.007315)	<2e-16 ***
EURO 2	Log (NO_x g/km) = 0.306263 - 0.333924 * log (average speed km/h)	0.2989	0.61	0.306263 (0.018019)	<2e-16 ***	- 0.333924 (0.007185)	<2e-16 ***
EURO 3	Log (NO_x g/km) = - 0.488252 - 0.465874 * log (average speed km/h)	0.2377	0.83	- 0.488252 (0.014330)	<2e-16 ***	- 0.465874 (0.005714)	<2e-16 ***
EURO 4	Log (NO_x g/km) = - 1.302957 - 0.329555 * log (average speed km/h)	0.2326	0.71	- 1.302957 (0.014026)	<2e-16 ***	- 0.329555 (0.005592)	<2e-16 ***
EURO 5	Log (NO_x g/km) = - 2.322750 - 0.331683 * log (average speed km/h)	0.2330	0.72	- 2.322750 (0.014048)	<2e-16 ***	- 0.331683 (0.005601)	<2e-16 ***
Diesel City Buses – Single-Decker							

EURO emission standard	Average-speed-emission function (PHEM-based)	Residual standard error	Adjusted R-squared (R^2)	Intercept (standard error)	Intercept variable p-value	Log average speed coefficient (standard error)	Log average speed variable p-value
EURO 0	Log (NO_x g/km) = 4.676692 - 0.700805 * log (average speed km/h)	0.1639	0.96	4.676692 (0.009879)	<2e-16 ***	- 0.700805 (0.003941)	<2e-16 ***
EURO I	Log (NO_x g/km) = 4.492894 - 0.743899 * log (average speed km/h)	0.1417	0.97	4.492894 (0.008540)	<2e-16 ***	- 0.743899 (0.003407)	<2e-16 ***
EURO II	Log (NO_x g/km) = 4.672739 - 0.760159 * log (average speed km/h)	0.1246	0.98	4.672739 (0.007512)	<2e-16 ***	- 0.760159 (0.002996)	<2e-16 ***
EURO III	Log (NO_x g/km) = 4.840677 - 0.873602 * log (average speed km/h)	0.1048	0.99	4.840677 (0.006321)	<2e-16 ***	- 0.873602 (0.002522)	<2e-16 ***
EURO IV	Log (NO_x g/km) = 3.572350 - 0.607050 * log (average speed km/h)	0.1604	0.95	3.572350 (0.009669)	<2e-16 ***	- 0.607050 (0.003858)	<2e-16 ***
EURO V EGR	Log (NO_x g/km) = 3.799527 - 0.736110 * log (average speed km/h)	0.1580	0.96	3.799527 (0.009525)	<2e-16 ***	- 0.736110 (0.003801)	<2e-16 ***
EURO V SCR	Log (NO_x g/km) = 4.25045 - 0.92618 * log (average speed km/h)	0.2565	0.94	4.25045 (0.01546)	<2e-16 ***	- 0.92618 (0.00617)	<2e-16 ***
Diesel City Buses – Double-Decker							
EURO emission standard	Average-speed-emission function (PHEM-based)	Residual standard error	Adjusted R-squared (R^2)	Intercept (standard error)	Intercept variable p-value	Log average speed coefficient (standard error)	Log average speed variable p-value
EURO 0	Log (NO_x g/km) = 4.864863 - 0.678139 * log (average speed km/h)	0.1740	0.95	4.864863 (0.010492)	<2e-16 ***	- 0.678139 (0.004187)	<2e-16 ***
EURO I	Log (NO_x g/km) = 4.680974 - 0.723172 * log (average speed km/h)	0.1508	0.97	4.680974 (0.009091)	<2e-16 ***	- 0.723172 (0.003628)	<2e-16 ***
EURO II	Log (NO_x g/km) = 4.689974 - 0.717973 * log (average speed km/h)	0.1431	0.97	4.689974 (0.008625)	<2e-16 ***	- 0.717973 (0.003442)	<2e-16 ***
EURO III	Log (NO_x g/km) = 5.031918 - 0.855972 * log (average speed km/h)	0.1115	0.99	5.031918 (0.006722)	<2e-16 ***	- 0.855972 (0.002683)	<2e-16 ***
EURO IV	Log (NO_x g/km) = 3.769395 - 0.583561 * log (average speed km/h)	0.1627	0.94	3.769395 (0.009807)	<2e-16 ***	- 0.583561 (0.003915)	<2e-16 ***
EURO V EGR	Log (NO_x g/km) = 4.000345 - 0.718881 * log (average speed km/h)	0.1596	0.96	4.000345 (0.009621)	<2e-16 ***	- 0.718881 (0.003841)	<2e-16 ***
EURO V SCR	Log (NO_x g/km) = 4.502763 - 0.977618 * log (average speed km/h)	0.2887	0.93	4.502763 (0.017399)	<2e-16 ***	- 0.977618 (0.006948)	<2e-16 ***
Diesel Coaches – Small (≤ 18 tonnes)							
EURO emission standard	Average-speed-emission function (PHEM-based)	Residual standard error	Adjusted R-squared (R^2)	Intercept (standard error)	Intercept variable p-value	Log average speed coefficient (standard error)	Log average speed variable p-value
EURO 0	Log (NO_x g/km) = 5.359587 - 0.762523 * log (average speed km/h)	0.1555	0.97	5.359587 (0.009375)	<2e-16 ***	- 0.762523 (0.003739)	<2e-16 ***
EURO I	Log (NO_x g/km) = 5.117792 - 0.805469 * log (average speed km/h)	0.1454	0.98	5.117792 (0.008767)	<2e-16 ***	- 0.805469 (0.003496)	<2e-16 ***
EURO II	Log (NO_x g/km) = 5.131610 - 0.799404 * log (average speed km/h)	0.1333	0.98	5.131610 (0.008035)	<2e-16 ***	- 0.799404 (0.003205)	<2e-16 ***
EURO III	Log (NO_x g/km) = 5.282824 - 0.894602 * log (average speed km/h)	0.1249	0.99	5.282824 (0.007512)	<2e-16 ***	- 0.894602 (0.002996)	<2e-16 ***
EURO IV	Log (NO_x g/km) = 4.520104 - 0.782564 * log (average speed km/h)	0.1595	0.97	4.520104 (0.009574)	<2e-16 ***	- 0.782564 (0.003820)	<2e-16 ***
EURO V EGR	Log (NO_x g/km) = 4.708945 - 0.888890 * log (average speed km/h)	0.1305	0.98	4.708945 (0.007816)	<2e-16 ***	- 0.888890 (0.003120)	<2e-16 ***
EURO V SCR	Log (NO_x g/km) = 5.194908 - 1.091808 * log (average speed km/h)	0.2242	0.97	5.194908 (0.013406)	<2e-16 ***	- 1.091808 (0.005351)	<2e-16 ***
Diesel Coaches – Large (> 18 tonnes)							
EURO emission standard	Average-speed-emission function (PHEM-based)	Residual standard error	Adjusted R-squared (R^2)	Intercept (standard error)	Intercept variable p-value	Log average speed coefficient (standard error)	Log average speed variable p-value
EURO 0	Log (NO_x g/km) = 5.528112 - 0.749336 * log (average speed km/h)	0.1582	0.97	5.528112 (0.009540)	<2e-16 ***	- 0.749336 (0.003805)	<2e-16 ***
EURO I	Log (NO_x g/km) = 5.308916 - 0.797025 * log (average speed km/h)	0.1465	0.97	5.308916 (0.008834)	<2e-16 ***	- 0.797025 (0.003523)	<2e-16 ***
EURO II	Log (NO_x g/km) = 5.391377 - 0.801935 * log (average speed km/h)	0.1295	0.98	5.391377 (0.007809)	<2e-16 ***	- 0.801935 (0.003114)	<2e-16 ***
EURO III	Log (NO_x g/km) = 5.592120 - 0.907643 * log (average speed km/h)	0.1217	0.99	5.592120 (0.007338)	<2e-16 ***	- 0.907643 (0.002926)	<2e-16 ***
EURO IV	Log (NO_x g/km) = 4.800981 - 0.787978 * log (average speed km/h)	0.1467	0.97	4.800981 (0.008842)	<2e-16 ***	- 0.787978 (0.003526)	<2e-16 ***
EURO V EGR	Log (NO_x g/km) = 5.037819 - 0.899207 * log (average speed km/h)	0.1193	0.99	5.037819 (0.007195)	<2e-16 ***	- 0.899207 (0.002869)	<2e-16 ***
EURO V SCR	Log (NO_x g/km) = 5.474739 - 1.048355 * log (average speed km/h)	0.1864	0.98	5.474739 (0.011238)	<2e-16 ***	- 1.048355 (0.004482)	<2e-16 ***

Diesel Rigid Heavy Duty Vehicles – 0-7.5 tonnes							
EURO emission standard	Average-speed-emission function (PHEM-based)	Residual standard error	Adjusted R-squared (R^2)	Intercept (standard error)	Intercept variable p-value	Log average speed coefficient (standard error)	Log average speed variable p-value
EURO 0	Log (NO_x g/km) = 4.247470 - 0.616907 * log (average speed km/h)	0.1767	0.94	4.247470 (0.010641)	<2e-16 ***	- 0.616907 (0.004246)	<2e-16 ***
EURO I	Log (NO_x g/km) = 3.858387 - 0.668880 * log (average speed km/h)	0.1775	0.95	3.858387 (0.010693)	<2e-16 ***	- 0.668880 (0.004267)	<2e-16 ***
EURO II	Log (NO_x g/km) = 3.871804 - 0.659312 * log (average speed km/h)	0.1640	0.95	3.871804 (0.009876)	<2e-16 ***	- 0.659312 (0.003941)	<2e-16 ***
EURO III	Log (NO_x g/km) = 4.057017 - 0.768027 * log (average speed km/h)	0.1704	0.96	4.057017 (0.010261)	<2e-16 ***	- 0.768027 (0.004094)	<2e-16 ***
EURO IV	Log (NO_x g/km) = 3.281848 - 0.643211 * log (average speed km/h)	0.1952	0.93	3.281848 (0.011746)	<2e-16 ***	- 0.643211 (0.004688)	<2e-16 ***
EURO V EGR	Log (NO_x g/km) = 3.488096 - 0.752954 * log (average speed km/h)	0.1731	0.96	3.488096 (0.010414)	<2e-16 ***	- 0.752954 (0.004157)	<2e-16 ***
EURO V SCR	Log (NO_x g/km) = 4.017415 - 0.934690 * log (average speed km/h)	0.2115	0.96	4.017415 (0.012719)	<2e-16 ***	- 0.934690 (0.005077)	<2e-16 ***
Diesel Rigid Heavy Duty Vehicles – 7.5-12 tonnes							
EURO emission standard	Average-speed-emission function (PHEM-based)	Residual standard error	Adjusted R-squared (R^2)	Intercept (standard error)	Intercept variable p-value	Log average speed coefficient (standard error)	Log average speed variable p-value
EURO 0	Log (NO_x g/km) = 4.35013 - 0.58253 * log (average speed km/h)	0.1797	0.93	4.35013 (0.01082)	<2e-16 ***	- 0.58253 (0.00432)	<2e-16 ***
EURO I	Log (NO_x g/km) = 3.95086 - 0.63131 * log (average speed km/h)	0.1818	0.94	3.95086 (0.01095)	<2e-16 ***	- 0.63131 (0.00437)	<2e-16 ***
EURO II	Log (NO_x g/km) = 3.970967 - 0.627020 * log (average speed km/h)	0.1658	0.95	3.970967 (0.009986)	<2e-16 ***	- 0.627020 (0.003985)	<2e-16 ***
EURO III	Log (NO_x g/km) = 4.154033 - 0.734781 * log (average speed km/h)	0.1740	0.96	4.154033 (0.010480)	<2e-16 ***	- 0.734781 (0.004183)	<2e-16 ***
EURO IV	Log (NO_x g/km) = 3.38612 - 0.60716 * log (average speed km/h)	0.1953	0.92	3.38612 (0.01175)	<2e-16 ***	- 0.60716 (0.00469)	<2e-16 ***
EURO V EGR	Log (NO_x g/km) = 3.593042 - 0.726982 * log (average speed km/h)	0.1722	0.96	3.593042 (0.010361)	<2e-16 ***	- 0.726982 (0.004136)	<2e-16 ***
EURO V SCR	Log (NO_x g/km) = 4.202341 - 0.997859 * log (average speed km/h)	0.2555	0.95	4.202341 (0.015364)	<2e-16 ***	- 0.997859 (0.006134)	<2e-16 ***
Diesel Rigid Heavy Duty Vehicles – 12-14 tonnes							
EURO emission standard	Average-speed-emission function (PHEM-based)	Residual standard error	Adjusted R-squared (R^2)	Intercept (standard error)	Intercept variable p-value	Log average speed coefficient (standard error)	Log average speed variable p-value
EURO 0	Log (NO_x g/km) = 4.377455 - 0.572182 * log (average speed km/h)	0.181	0.93	4.377455 (0.010905)	<2e-16 ***	- 0.572182 (0.004353)	<2e-16 ***
EURO I	Log (NO_x g/km) = 3.975865 - 0.620161 * log (average speed km/h)	0.1833	0.93	3.975865 (0.011041)	<2e-16 ***	- 0.620161 (0.004407)	<2e-16 ***
EURO II	Log (NO_x g/km) = 3.997376 - 0.617059 * log (average speed km/h)	0.167	0.94	3.997376 (0.010059)	<2e-16 ***	- 0.617059 (0.004015)	<2e-16 ***
EURO III	Log (NO_x g/km) = 4.180340 - 0.725159* log (average speed km/h)	0.1754	0.96	4.180340 (0.010566)	<2e-16 ***	- 0.725159 (0.004217)	<2e-16 ***
EURO IV	Log (NO_x g/km) = 3.41743 - 0.59710 * log (average speed km/h)	0.1956	0.92	3.41743 (0.01177)	<2e-16 ***	- 0.59710 (0.00470)	<2e-16 ***
EURO V EGR	Log (NO_x g/km) = 3.622997 - 0.718972 * log (average speed km/h)	0.1725	0.96	3.622997 (0.010379)	<2e-16 ***	- 0.718972 (0.004144)	<2e-16 ***
EURO V SCR	Log (NO_x g/km) = 4.256352 - 1.019481 * log (average speed km/h)	0.2721	0.95	4.256352 (0.016362)	<2e-16 ***	- 1.019481 (0.006533)	<2e-16 ***
Diesel Rigid Heavy Duty Vehicles – 14-20 tonnes							
EURO emission standard	Average-speed-emission function (PHEM-based)	Residual standard error	Adjusted R-squared (R^2)	Intercept (standard error)	Intercept variable p-value	Log average speed coefficient (standard error)	Log average speed variable p-value
EURO 0	Log (NO_x g/km) = 4.627393 - 0.587858 * log (average speed km/h)	0.174	0.93	4.627393 (0.010492)	<2e-16 ***	- 0.587858 (0.004185)	<2e-16 ***
EURO I	Log (NO_x g/km) = 4.227274 - 0.636060 * log (average speed km/h)	0.1756	0.94	4.227274 (0.010589)	<2e-16 ***	- 0.636060 (0.004224)	<2e-16 ***
EURO II	Log (NO_x g/km) = 4.248947 - 0.630082 * log (average speed km/h)	0.1614	0.95	4.248947 (0.009734)	<2e-16 ***	- 0.630082 (0.003883)	<2e-16 ***
EURO III	Log (NO_x g/km) = 4.435325 - 0.739722* log (average speed km/h)	0.1694	0.96	4.435325 (0.010210)	<2e-16 ***	- 0.739722 (0.004073)	<2e-16 ***
EURO IV	Log (NO_x g/km) = 3.627890 - 0.602790 * log (average speed km/h)	0.1889	0.93	3.627890 (0.011377)	<2e-16 ***	- 0.602790 (0.004541)	<2e-16 ***
EURO V EGR	Log (NO_x g/km) = 3.854184 - 0.725849* log (average speed km/h)	0.165	0.96	3.854184 (0.009937)	<2e-16 ***	- 0.725849 (0.003966)	<2e-16 ***

EURO V SCR	Log (NO_x g/km) = 4.451131 - 0.963657* log (average speed km/h)	0.2312	0.96	4.451131 (0.013922)	<2e-16 ***	- 0.963657 (0.005556)	<2e-16 ***
Diesel Rigid Heavy Duty Vehicles – 20-26 tonnes							
EURO emission standard	Average-speed-emission function (PHEM-based)	Residual standard error	Adjusted R-squared (R^2)	Intercept (standard error)	Intercept variable p-value	Log average speed coefficient (standard error)	Log average speed variable p-value
EURO 0	Log (NO_x g/km) = 4.66896 - 0.55725 * log (average speed km/h)	0.1974	0.91	4.66896 (0.01191)	<2e-16 ***	- 0.55725 (0.00475)	<2e-16 ***
EURO I	Log (NO_x g/km) = 4.450260 - 0.610717 * log (average speed km/h)	0.1831	0.93	4.450260 (0.011042)	<2e-16 ***	- 0.610717 (0.004405)	<2e-16 ***
EURO II	Log (NO_x g/km) = 4.470563 - 0.611105 * log (average speed km/h)	0.1703	0.94	4.470563 (0.010270)	<2e-16 ***	- 0.611105 (0.004097)	<2e-16 ***
EURO III	Log (NO_x g/km) = 4.585696 - 0.703057* log (average speed km/h)	0.1781	0.95	4.585696 (0.010739)	<2e-16 ***	- 0.703057 (0.004284)	<2e-16 ***
EURO IV	Log (NO_x g/km) = 3.874854 - 0.596535 * log (average speed km/h)	0.2010	0.92	3.874854 (0.012089)	<2e-16 ***	- 0.596535 (0.004825)	<2e-16 ***
EURO V EGR	Log (NO_x g/km) = 4.123483 - 0.737964* log (average speed km/h)	0.1685	0.96	4.123483 (0.010133)	<2e-16 ***	- 0.737964 (0.004046)	<2e-16 ***
EURO V SCR	Log (NO_x g/km) = 4.724692 - 1.016208* log (average speed km/h)	0.263	0.95	4.724692 (0.015810)	<2e-16 ***	- 1.016208 (0.006313)	<2e-16 ***
Diesel Rigid Heavy Duty Vehicles – 26-28 tonnes							
EURO emission standard	Average-speed-emission function (PHEM-based)	Residual standard error	Adjusted R-squared (R^2)	Intercept (standard error)	Intercept variable p-value	Log average speed coefficient (standard error)	Log average speed variable p-value
EURO 0	Log (NO_x g/km) = 4.729494 - 0.533261 * log (average speed km/h)	0.2022	0.90	4.729494 (0.012198)	<2e-16 ***	- 0.533261 (0.004868)	<2e-16 ***
EURO I	Log (NO_x g/km) = 4.509132 - 0.588109 * log (average speed km/h)	0.1878	0.92	4.509132 (0.011325)	<2e-16 ***	- 0.588109 (0.004519)	<2e-16 ***
EURO II	Log (NO_x g/km) = 4.531899 - 0.591304 * log (average speed km/h)	0.1733	0.94	4.531899 (0.010451)	<2e-16 ***	- 0.591304 (0.004171)	<2e-16 ***
EURO III	Log (NO_x g/km) = 4.645106 - 0.681778 * log (average speed km/h)	0.1824	0.95	4.645106 (0.010995)	<2e-16 ***	- 0.681778 (0.004388)	<2e-16 ***
EURO IV	Log (NO_x g/km) = 3.943759 - 0.576985 * log (average speed km/h)	0.2026	0.91	3.943759 (0.012188)	<2e-16 ***	- 0.576985 (0.004866)	<2e-16 ***
EURO V EGR	Log (NO_x g/km) = 4.190391 - 0.723581* log (average speed km/h)	0.1696	0.96	4.190391 (0.010198)	<2e-16 ***	- 0.723581 (0.004074)	<2e-16 ***
EURO V SCR	Log (NO_x g/km) = 4.83229 - 1.05597* log (average speed km/h)	0.2816	0.95	4.83229 (0.01692)	<2e-16 ***	- 1.05597 (0.00676)	<2e-16 ***
Diesel Rigid Heavy Duty Vehicles – 28-32 tonnes							
EURO emission standard	Average-speed-emission function (PHEM-based)	Residual standard error	Adjusted R-squared (R^2)	Intercept (standard error)	Intercept variable p-value	Log average speed coefficient (standard error)	Log average speed variable p-value
EURO 0	Log (NO_x g/km) = 4.902552 - 0.542198 * log (average speed km/h)	0.1988	0.90	4.902552 (0.011986)	<2e-16 ***	- 0.542198 (0.004782)	<2e-16 ***
EURO I	Log (NO_x g/km) = 4.681982 - 0.596487 * log (average speed km/h)	0.1845	0.93	4.681982 (0.011125)	<2e-16 ***	- 0.596487 (0.004439)	<2e-16 ***
EURO II	Log (NO_x g/km) = 4.706210 - 0.598926 * log (average speed km/h)	0.1706	0.94	4.706210 (0.010290)	<2e-16 ***	- 0.598926 (0.004106)	<2e-16 ***
EURO III	Log (NO_x g/km) = 4.818953 - 0.689773 * log (average speed km/h)	0.1799	0.95	4.818953 (0.010847)	<2e-16 ***	- 0.689773 (0.004328)	<2e-16 ***
EURO IV	Log (NO_x g/km) = 4.098997 - 0.580529 * log (average speed km/h)	0.1984	0.91	4.098997 (0.011965)	<2e-16 ***	- 0.580529 (0.004774)	<2e-16 ***
EURO V EGR	Log (NO_x g/km) = 4.351699 - 0.724230* log (average speed km/h)	0.1694	0.96	4.351699 (0.010213)	<2e-16 ***	- 0.724230 (0.004075)	<2e-16 ***
EURO V SCR	Log (NO_x g/km) = 4.974251 - 1.028398 * log (average speed km/h)	0.2683	0.95	4.974251 (0.016158)	<2e-16 ***	- 1.028398 (0.006449)	<2e-16 ***
Diesel Rigid Heavy Duty Vehicles – > 32 tonnes							
EURO emission standard	Average-speed-emission function (PHEM-based)	Residual standard error	Adjusted R-squared (R^2)	Intercept (standard error)	Intercept variable p-value	Log average speed coefficient (standard error)	Log average speed variable p-value
EURO 0	Log (NO_x g/km) = 4.949774 - 0.495273 * log (average speed km/h)	0.2095	0.87	4.949774 (0.012635)	<2e-16 ***	- 0.495273 (0.005046)	<2e-16 ***
EURO I	Log (NO_x g/km) = 4.726877 - 0.552286 * log (average speed km/h)	0.1957	0.91	4.726877 (0.011804)	<2e-16 ***	- 0.552286 (0.004714)	<2e-16 ***
EURO II	Log (NO_x g/km) = 4.755083 - 0.560964 * log (average speed km/h)	0.1788	0.92	4.755083 (0.010785)	<2e-16 ***	- 0.560964 (0.004307)	<2e-16 ***
EURO III	Log (NO_x g/km) = 4.86492 - 0.64768 * log (average speed km/h)	0.1889	0.94	4.86492 (0.01139)	<2e-16 ***	- 0.64768 (0.00455)	<2e-16 ***
EURO IV	Log (NO_x g/km) = 4.170436 - 0.545215 * log (average speed km/h)	0.2036	0.90	4.170436 (0.012251)	<2e-16 ***	- 0.545215 (0.004895)	<2e-16 ***

EURO V EGR	Log (NO_x g/km) = 4.414476 - 0.699178 * log (average speed km/h)	0.1708	0.95	4.414476 (0.010278)	<2e-16 ***	- 0.699178 (0.004108)	<2e-16 ***
EURO V SCR	Log (NO_x g/km) = 5.103652 - 1.101341 * log (average speed km/h)	0.3109	0.94	5.103652 (0.018697)	<2e-16 ***	- 1.101341 (0.007474)	<2e-16 ***
Diesel Articulated Heavy Duty Vehicles – 14-20 tonnes							
EURO emission standard	Average-speed-emission function (PHEM-based)	Residual standard error	Adjusted R-squared (R^2)	Intercept (standard error)	Intercept variable p-value	Log average speed coefficient (standard error)	Log average speed variable p-value
EURO 0	Log (NO_x g/km) = 4.606537 - 0.616872 * log (average speed km/h)	0.1668	0.95	4.606537 (0.010058)	<2e-16 ***	- 0.616872 (0.004011)	<2e-16 ***
EURO I	Log (NO_x g/km) = 4.213917 - 0.667917 * log (average speed km/h)	0.1681	0.95	4.213917 (0.010134)	<2e-16 ***	- 0.667917 (0.004041)	<2e-16 ***
EURO II	Log (NO_x g/km) = 4.228455 - 0.655676 * log (average speed km/h)	0.1561	0.96	4.228455 (0.009413)	<2e-16 ***	- 0.655676 (0.003754)	<2e-16 ***
EURO III	Log (NO_x g/km) = 4.418745 - 0.767759 * log (average speed km/h)	0.1616	0.97	4.418745 (0.009745)	<2e-16 ***	- 0.767759 (0.003886)	<2e-16 ***
EURO IV	Log (NO_x g/km) = 3.597919 - 0.630018 * log (average speed km/h)	0.1851	0.94	3.597919 (0.011147)	<2e-16 ***	- 0.630018 (0.004447)	<2e-16 ***
EURO V EGR	Log (NO_x g/km) = 3.829788 - 0.746201 * log (average speed km/h)	0.1616	0.96	3.829788 (0.009737)	<2e-16 ***	- 0.746201 (0.003885)	<2e-16 ***
EURO V SCR	Log (NO_x g/km) = 4.35345 - 0.90410 * log (average speed km/h)	0.1910	0.97	4.35345 (0.01150)	<2e-16 ***	- 0.90410 (0.00459)	<2e-16 ***
Diesel Articulated Heavy Duty Vehicles – 20-28 tonnes							
EURO emission standard	Average-speed-emission function (PHEM-based)	Residual standard error	Adjusted R-squared (R^2)	Intercept (standard error)	Intercept variable p-value	Log average speed coefficient (standard error)	Log average speed variable p-value
EURO 0	Log (NO_x g/km) = 4.729403 - 0.567596 * log (average speed km/h)	0.1945	0.91	4.729403 (0.011728)	<2e-16 ***	- 0.567596 (0.004678)	<2e-16 ***
EURO I	Log (NO_x g/km) = 4.510232 - 0.620151 * log (average speed km/h)	0.1803	0.94	4.510232 (0.010871)	<2e-16 ***	- 0.620151 (0.004336)	<2e-16 ***
EURO II	Log (NO_x g/km) = 4.530409 - 0.619166 * log (average speed km/h)	0.1686	0.94	4.530409 (0.010169)	<2e-16 ***	- 0.619166 (0.004056)	<2e-16 ***
EURO III	Log (NO_x g/km) = 4.646895 - 0.712503 * log (average speed km/h)	0.1757	0.95	4.646895 (0.010597)	<2e-16 ***	- 0.712503 (0.004227)	<2e-16 ***
EURO IV	Log (NO_x g/km) = 3.928445 - 0.604350 * log (average speed km/h)	0.1989	0.92	3.928445 (0.011992)	<2e-16 ***	- 0.604350 (0.004783)	<2e-16 ***
EURO V EGR	Log (NO_x g/km) = 4.180084 - 0.741855 * log (average speed km/h)	0.1704	0.96	4.180084 (0.010276)	<2e-16 ***	- 0.741855 (0.004099)	<2e-16 ***
EURO V SCR	Log (NO_x g/km) = 4.757762 - 0.993963 * log (average speed km/h)	0.2523	0.95	4.757762 (0.015179)	<2e-16 ***	- 0.993963 (0.006058)	<2e-16 ***
Diesel Articulated Heavy Duty Vehicles – 28-34 tonnes							
EURO emission standard	Average-speed-emission function (PHEM-based)	Residual standard error	Adjusted R-squared (R^2)	Intercept (standard error)	Intercept variable p-value	Log average speed coefficient (standard error)	Log average speed variable p-value
EURO 0	Log (NO_x g/km) = 4.914491 - 0.588409 * log (average speed km/h)	0.1939	0.92	4.914491 (0.011690)	<2e-16 ***	- 0.588409 (0.004663)	<2e-16 ***
EURO I	Log (NO_x g/km) = 4.697038 - 0.644878 * log (average speed km/h)	0.1836	0.94	4.697038 (0.011068)	<2e-16 ***	- 0.644878 (0.004415)	<2e-16 ***
EURO II	Log (NO_x g/km) = 4.710468 - 0.631827 * log (average speed km/h)	0.1619	0.95	4.710468 (0.009760)	<2e-16 ***	- 0.631827 (0.003893)	<2e-16 ***
EURO III	Log (NO_x g/km) = 4.796667 - 0.687514 * log (average speed km/h)	0.1614	0.96	4.796667 (0.009732)	<2e-16 ***	- 0.687514 (0.003881)	<2e-16 ***
EURO IV	Log (NO_x g/km) = 4.07393 - 0.58793 * log (average speed km/h)	0.1962	0.92	4.07393 (0.01183)	<2e-16 ***	- 0.58793 (0.00472)	<2e-16 ***
EURO V EGR	Log (NO_x g/km) = 4.332277- 0.708734 * log (average speed km/h)	0.1737	0.95	4.332277 (0.010475)	<2e-16 ***	- 0.708734 (0.004179)	<2e-16 ***
EURO V SCR	Log (NO_x g/km) = 4.916851- 1.000390 * log (average speed km/h)	0.2209	0.96	4.916851 (0.013320)	<2e-16 ***	- 1.000390 (0.005313)	<2e-16 ***
Diesel Articulated Heavy Duty Vehicles – 34-40 tonnes							
EURO emission standard	Average-speed-emission function (PHEM-based)	Residual standard error	Adjusted R-squared (R^2)	Intercept (standard error)	Intercept variable p-value	Log average speed coefficient (standard error)	Log average speed variable p-value
EURO 0	Log (NO_x g/km) = 5.016284 - 0.546429 * log (average speed km/h)	0.2030	0.90	5.016284 (0.012241)	<2e-16 ***	- 0.546429 (0.004885)	<2e-16 ***
EURO I	Log (NO_x g/km) = 4.794115 - 0.604173 * log (average speed km/h)	0.1921	0.93	4.794115 (0.011584)	<2e-16 ***	- 0.604173 (0.004623)	<2e-16 ***
EURO II	Log (NO_x g/km) = 4.814710 - 0.599787 * log (average speed km/h)	0.1672	0.94	4.814710 (0.010086)	<2e-16 ***	- 0.599787 (0.004025)	<2e-16 ***
EURO III	Log (NO_x g/km) = 4.90247 - 0.65643 * log (average speed km/h)	0.1679	0.95	4.90247 (0.01013)	<2e-16 ***	- 0.65643 (0.00404)	<2e-16 ***

EURO IV	Log (NO_x g/km) = 4.187311 - 0.553426 * log (average speed km/h)	0.1987	0.91	4.187311 (0.011985)	<2e-16 ***	- 0.553426 (0.004783)	<2e-16 ***
EURO V EGR	Log (NO_x g/km) = 4.441064 - 0.682704 * log (average speed km/h)	0.1757	0.95	4.441064 (0.010594)	<2e-16 ***	- 0.682704 (0.004228)	<2e-16 ***
EURO V SCR	Log (NO_x g/km) = 5.093639 - 1.060296 * log (average speed km/h)	0.2528	0.96	5.093639 (0.015245)	<2e-16 ***	- 1.060296 (0.006084)	<2e-16 ***
Diesel Articulated Heavy Duty Vehicles – 40-50 tonnes							
EURO emission standard	Average-speed-emission function (PHEM-based)	Residual standard error	Adjusted R-squared (R^2)	Intercept (standard error)	Intercept variable p-value	Log average speed coefficient (standard error)	Log average speed variable p-value
EURO 0	Log (NO_x g/km) = 5.05108 - 0.52184 * log (average speed km/h)	0.2089	0.89	5.05108 (0.01260)	<2e-16 ***	- 0.52184 (0.00503)	<2e-16 ***
EURO I	Log (NO_x g/km) = 4.825463 - 0.580106 * log (average speed km/h)	0.1978	0.91	4.825463 (0.011934)	<2e-16 ***	- 0.580106 (0.004765)	<2e-16 ***
EURO II	Log (NO_x g/km) = 4.849699 - 0.580706 * log (average speed km/h)	0.171	0.93	4.849699 (0.010314)	<2e-16 ***	- 0.580706 (0.004118)	<2e-16 ***
EURO III	Log (NO_x g/km) = 4.938108 - 0.637497 * log (average speed km/h)	0.1716	0.95	4.938108 (0.010352)	<2e-16 ***	- 0.637497 (0.004132)	<2e-16 ***
EURO IV	Log (NO_x g/km) = 4.229131 - 0.533282 * log (average speed km/h)	0.2003	0.90	4.229131 (0.012081)	<2e-16 ***	- 0.533282 (0.004824)	<2e-16 ***
EURO V EGR	Log (NO_x g/km) = 4.479732 - 0.668162 * log (average speed km/h)	0.1778	0.95	4.479732 (0.010727)	<2e-16 ***	- 0.668162 (0.004283)	<2e-16 ***
EURO V SCR	Log (NO_x g/km) = 5.161479 - 1.090896 * log (average speed km/h)	0.2726	0.95	5.161479 (0.016445)	<2e-16 ***	- 1.090896 (0.006566)	<2e-16 ***
All logs are natural logs of the base e; '***' significant at the 0.001 level.							

4.4.3. Comparison with COPERT's Average-Speed-Emission Functions

The 164 newly developed average-speed-emission functions (Table 18) were compared to their corresponding functions sourced from COPERT 4 v10.0, as described in Section 4.3.9. COPERT functions were also coded onto the Excel spreadsheet containing the newly developed functions. The Excel spreadsheet (which is being made open access) allows the user to enter the average link-based vehicle speed (km/h) to calculate, from both methods, the NO_x EF (g/km) for each 164 vehicle classes. To compare both methods, hypothetical speeds ranging from 1 km/h to 80 km/h were entered in the Excel spreadsheet in 1 km/h increments (i.e. 1,2,3,4, 5…,80 km/h). The range (1-80 km/h) was chosen as it reflects the modelled traffic speed range on the Bradford road network (Chapter 3). The spreadsheet calculated, from both methods, the NO_x EFs at each of the input speeds. The results of this exercise for passenger cars, as an example, are presented in Table 19 and Figure 51. The key results for the remaining vehicle classes are overviewed next.

1. **Diesel and Petrol Passenger Cars**

For diesel passenger cars, emissions calculated from the newly developed average-speed-emission functions differed than those calculated from COPERT as follows: the minimum EFs were lower, and the maximum EFs were higher, than COPERT, widening the range (Table 19). The differences in emissions were generally observed at speeds lower than 10 km/h, where the newly developed functions produced higher EFs than COPERT. However, this trend was reversed with increasing speeds (Figure 51); where COPERT produced higher EFs. In the case of EURO 3 and EURO 4 diesel vehicles, both models estimated EFs higher than European vehicle emission standards.

For petrol passenger cars, the minimum EFs from the newly developed average-speed-emission functions were higher (except for EURO 0 and EURO 3), than COPERT, narrowing the lower end of the range, and the maximum EFs were higher (expect for EURO 0), than COPERT, widening the upper end of the range. The differences in emissions factors were generally observed at speeds lower than 10 km/h, where the newly developed functions estimated higher EFs than the COPERT functions, and the differences were smaller with increasing speeds (Figure 51). Estimated EFs for petrol vehicles were closer to the European vehicle emission standards, when compared to diesel, and were significantly lower than diesel passenger cars EFs, for example by up to an order of magnitude. The reason behind the large discrepancy between petrol pre-EURO cars is unknown but estimates of these older vehicles are uncertain due to the limited underlying model data and the difficulty in measuring/modelling very low petrol NO_x emissions.

2. Diesel and Petrol Light Duty Vehicles

For diesel LDVs, across all weight classes (class I, II and III), emissions calculated from the newly developed average-speed-emission functions differed than those calculated from COPERT as follows: the minimum EFs were lower, and the maximum EFs were higher, than COPERT, widening the range. The differences in emissions were generally observed at speeds lower than 10 km/h, where the newly developed functions estimated higher EFs than COPERT, but this difference was reversed with increasing speeds. For the higher weight classes, there was evidence that COPERT estimated higher EFs especially for the older vehicle emission standards e.g. EURO 0 and EURO 1. In the case of the older emission standards EURO 0 and EURO 1, the COPERT EFs were higher than the PHEM-based ones, but these values are considered more uncertain due to the limited data available for older vehicle categories. For EURO 4 and EURO 5 LDVs, both models consistently estimated EFs higher than European vehicle emission standards.

For petrol LDVs, it was not possible to fit new PHEM-based average-speed-emission functions to the EURO 0 vehicles, across all weight classes. For the other vehicle emission standards, across all weight classes, emissions calculated from the newly developed average-speed-emission functions differed than those calculated from COPERT as follows: the minimum EFs were higher (except for EURO 3 and EURO 5), than COPERT, narrowing the lower end of the range, and the maximum EFs were higher (expect for EURO 5 class I), than COPERT, widening the upper end of the range. The key differences in emissions were generally observed at speeds lower than 10 km/h, where the newly developed functions estimated higher EFs than COPERT, and the differences were smaller with increasing speeds. Estimated EFs for petrol LDVs were closer to the European vehicle emission standards, when compared to diesel, and were significantly lower than diesel LDVs, for example by up to an order of magnitude.

3. Diesel City Buses

For Single-Decker buses, emissions calculated from the newly developed average-speed-emission functions differed than those calculated from COPERT as follows:

the minimum EFs were lower than COPERT (except for EURO 4 and EURO 5 EGR), widening the range from the lower end. The trends in the maximum EFs were mixed. The differences in emissions were generally observed at speeds lower than 30 km/h, where the newly developed functions produced slightly higher EFs than COPERT, but this difference was reversed with increasing speeds. Overall, estimates from both models were remarkably similar.

For Double-Decker buses, the minimum EFs were lower than COPERT (except for EURO 4 and EURO 5 EGR), widening the range from the lower end. The trends in the maximum EFs were mixed. The differences in emissions were generally observed at speeds lower than 20 km/h, where the newly developed functions produced slightly higher EFs than COPERT, but this difference was smaller and reversed with increasing speeds. Overall, estimates from both models were remarkably similar.

4. Diesel Coaches

For small coaches, emissions calculated from the newly developed average-speed-emission functions differed than those calculated from COPERT as follows: the minimum EFs were lower and the maximum EFs were higher (except for EURO 2 and EURO 3) than COPERT, widening the range. The differences in emissions were generally observed at speeds lower than 30 km/h, where the newly developed functions produced slightly higher EFs than COPERT, but estimates were remarkably similar with increasing speeds. For large coaches, the minimum EFs estimated from the newly developed average-speed-emission functions were lower (expect for EURO 5 EGR), and the maximum EFs were higher than COPERT, widening the range. The differences in emissions were generally observed at speeds lower than 30 km/h, where the newly developed functions produced slightly higher EFs than COPERT, but the estimates were more similar with increasing speeds.

5. Diesel Rigid and Articulated Heavy Duty Vehicles

For Rigid HDVs, trends in the minimum EFs estimated by the newly developed average-speed-emission functions were mixed while the maximum EFs were generally higher than COPERT, widening the range from the upper end. The differences in EFs were generally observed at speeds lower than 40 km/h, where the newly developed functions produced higher EFs than COPERT, but the estimates were more similar with increasing speeds. The differences were most apparent for the highest weight category (e.g. > 32 tonnes). Similar trends were observed in the case of Articulated HDVs.

Table 19 COPERT and PHEM-based NO_x Emission Estimates (g/km) Summary Statistics (Speed Range 1-80 km/h) – Passenger Cars

Diesel Passenger Cars EURO 1 (E1) to EURO 4 (E4)										
Statistic			COPERT E1	PHEM E1	COPERT E2	PHEM E2	COPERT E3	PHEM E3	COPERT E4	PHEM E4
Minimum			0.5540	0.3099	0.5544	0.3512	0.6642	0.3582	0.4233	0.2614
1st quartile			0.5633	0.3691	0.5650	0.4192	0.6708	0.4175	0.4383	0.3194
Median			0.6003	0.4715	0.6467	0.5372	0.7135	0.5176	0.5350	0.4227
Mean			0.7486	0.6913	0.7831	0.7940	0.8122	0.7038	0.6039	0.6854
3rd quartile			0.8483	0.7123	0.9298	0.8157	0.8908	0.7431	0.7536	0.6778
Maximum			1.3025	4.6216	1.3361	5.4167	1.2114	3.8277	0.9212	5.7612
Petrol Passenger Cars pre-EURO (E0) to EURO 4 (E4)										
Statistic	COPERT E0	PHEM E0	COPERT E1	PHEM E1	COPERT E2	PHEM E2	COPERT E3	PHEM E3	COPERT E4	PHEM E4
Minimum	2.243	0.4112	0.2577	0.2581	0.1426	0.1538	0.05589	0.04848	0.02536	0.03425
1st quartile	2.270	0.4448	0.2674	0.2781	0.1475	0.1745	0.06571	0.05501	0.03689	0.03881
Median	2.314	0.4964	0.2951	0.3089	0.1593	0.2084	0.07586	0.06566	0.05397	0.04624
Mean	2.432	0.5562	0.3220	0.3436	0.1827	0.2616	0.07515	0.08232	0.05757	0.05776
3rd quartile	2.549	0.5974	0.3576	0.3685	0.2160	0.2811	0.08488	0.08845	0.07659	0.06210
Maximum	3.009	1.3823	0.4771	0.8203	0.2717	1.0898	0.09113	0.34146	0.09859	0.23641

Figure 51 Bradford Average-Speed-Emission functions (blue lines) developed from analysis of micro-trips for Passenger cars sub-categories EURO 0 to EURO 4 compared with (raw) COPERT Average-Speed-Emission functions (red lines, no deterioration or fuel quality factor). [NOTE: European vehicle emission standards annotated as black straight line; note the different Y-axes scales for diesel and petrol cars], Source: Own Work (R)

<table>
<tr><th>FUEL</th><th colspan="5">PASSENGER CAR (Bradford Average) PHEM 11.7.2</th></tr>
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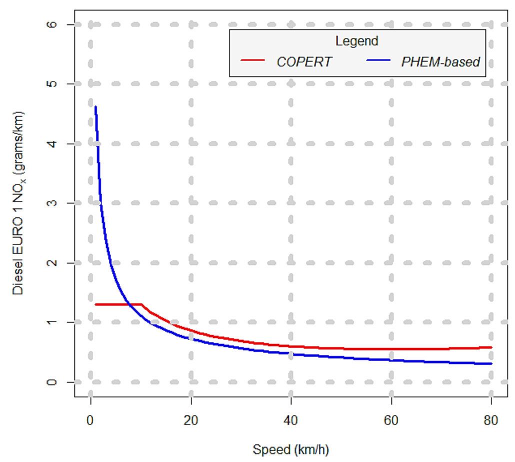
<td>
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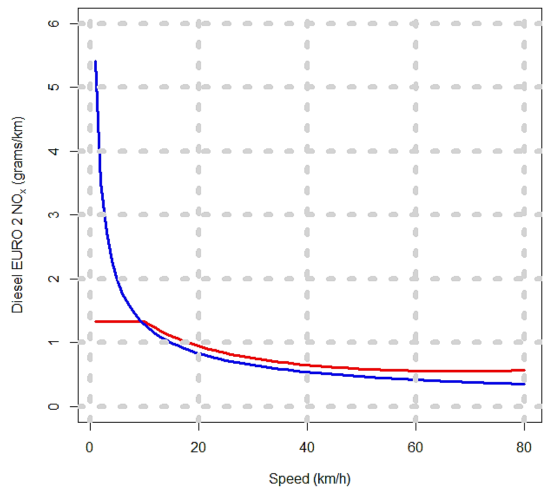
<td>
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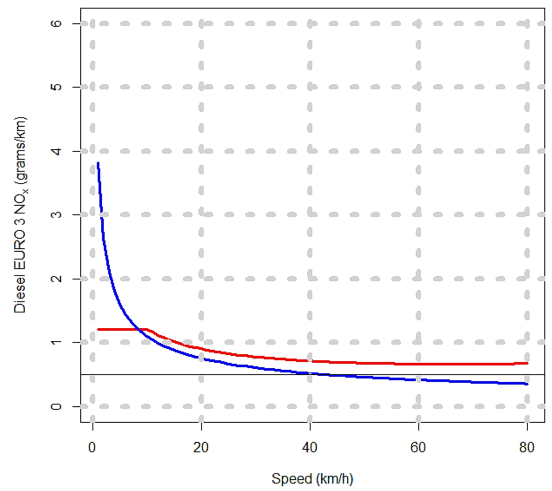
<td>
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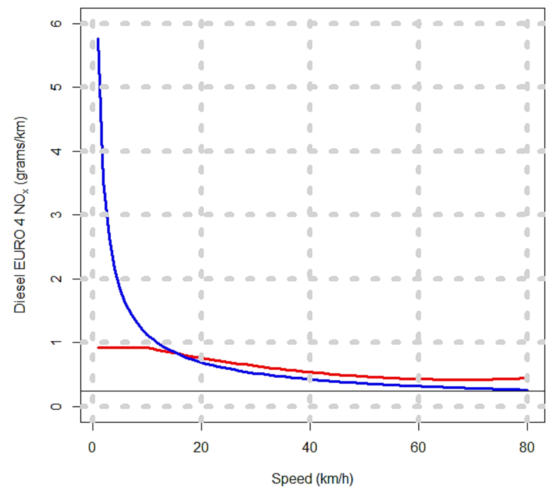
<td>
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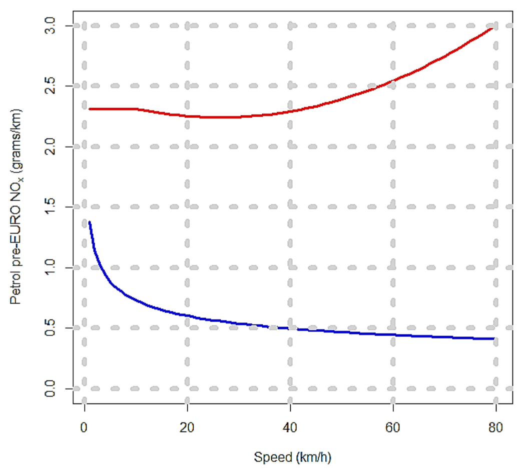
<td>
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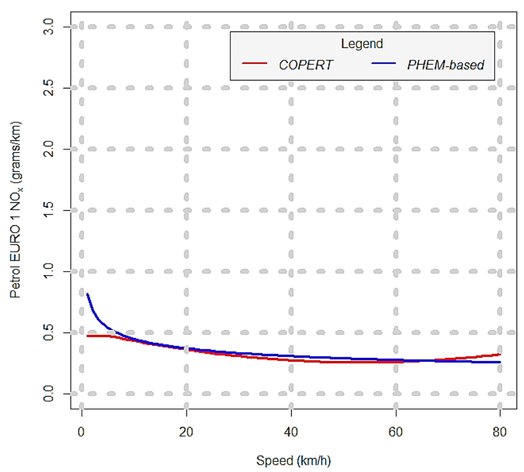
<td>
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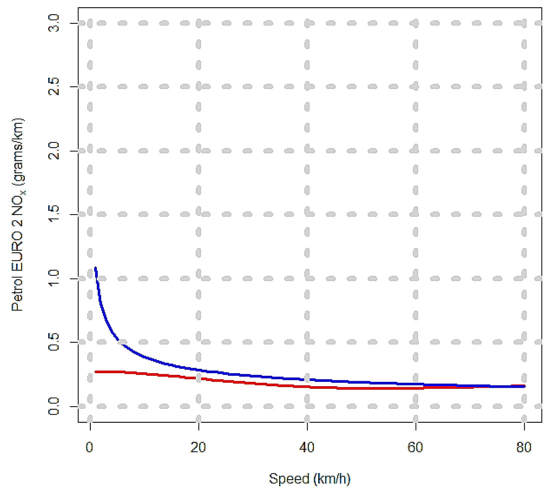
<td>
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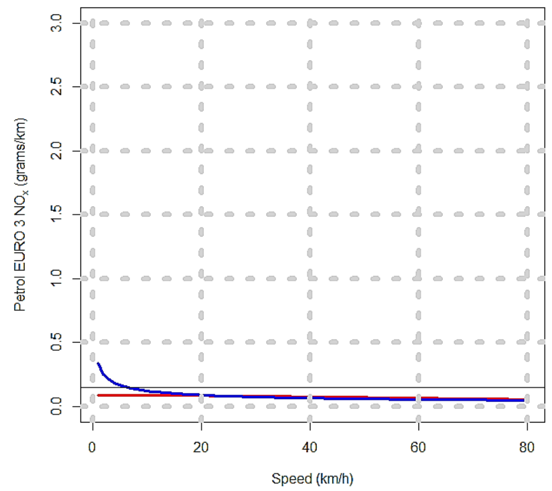
<td>
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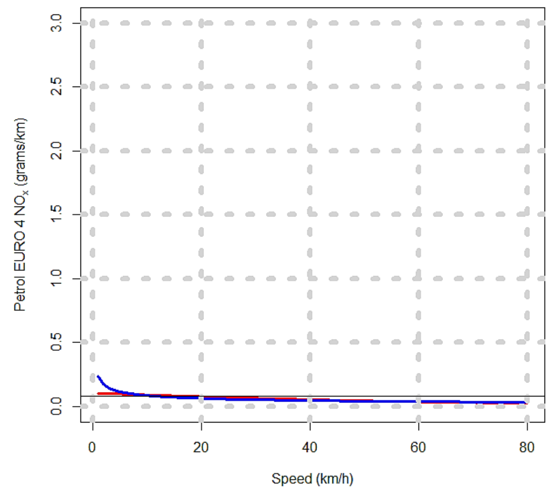
<td>
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4.5. Discussion

4.5.1. Summary

In this work, the instantaneous NO_x emissions from 167 vehicle classes were modelled in PHEM, using real-world and local instantaneous vehicle speed profiles, collected over 30 hours of driving in Bradford. Using the instantaneous NO_x emission estimates modelled in PHEM and a novel micro-trip analysis approach, 164 new NO_x average-speed-emission functions were developed for the full fleet of diesel and petrol Passenger cars, diesel and petrol LDVs, Buses, Coaches and Rigid and Articulated HDVs. The new NO_x average-speed-emission functions were developed for vehicles with emission standards pre-EURO to EURO 5/V, which were the emission standards operating in Bradford in year 2009, the main year of investigation. It was not possible to fit an acceptable function to 3 modelled pre-EURO petrol LDV classes (weight class I, II and III), and the standard functions sourced from COPERT were adopted for these vehicles. The limited underlying data for these older vehicle categories and the uncertainty associated with their low emissions are likely behind the high scatter precluding fitting an acceptable average-speed-emission function.

Unlike traditional methods, pairing the average speed and the corresponding average EF was undertaken at a micro-trip level (Figure 38), rather than at a 'trip' level (Figure 36). The newly developed functions fitted their underlying data well, and multiple parameters demonstrated only a few incidents (9 out of 164) where the new functions fitted the data poorly (R^2 value of < 0.7). This was in the case of older emission standards of petrol passenger cars and LDVs.

The newly developed functions were compared to the standard average-speed-emission functions used in the UK and sourced from the emission model COPERT. The key differences were observed at the low average speed segments (0-40 km/h, with the range depending on the vehicle type and exhaust after-treatment technology), where the newly developed functions generally estimated higher EFs than COPERT. This was a consistent observation in the case of HDVs, coaches and buses, but not passenger cars and LDVs where, in some instances, COPERT produced higher EFs at all speeds.

The range of the emission estimates from the newly developed functions differed from the range of emission estimates from COPERT, as the latter generally yielded smaller ranges as indicated by the minimum and maximum EF values. This indicates that the newly developed functions may result in more emissions variability over the road network, though further work is required to confirm this. The overall impact that the newly developed functions will have on Bradford's road transport emission inventories and air quality estimates is yet unclear and is explored in Chapter 5. The strengths and limitations of this approach, the potential for its future development and application and the planned next steps are overviewed next.

4.5.2. Strengths

The methodology underlying the development of the new NO_x average-speed-emission functions has several strengths. First, the driving cycles/vehicle speed profiles, which underlined the PHEM emission estimates, were real-world and local driving cycles, directly sourced from the study area where the new functions will be applied. The driving cycles collected covered a total distance of 650 km on multiple road types between the hours of 7:30 AM and 21:30 PM to account, as much as possible, for the full range of driving and traffic conditions. Therefore, the driving cycles underlying the PHEM estimates are thought to be broadly representative of, and tailored to, driving patterns in the study area.

The driving cycles obtained from the real-world diving in Bradford showed that idling time, acceleration and deceleration time are generally higher than accounted for in the current test type approval cycle. Furthermore, the maximum acceleration that was achieved in real-world driving was higher than its corresponding testing values and is very likely to be higher than acceleration values achieved in smoother laboratory testing and hence data underlying the development of laboratory-based emission models such as COPERT. As high acceleration events are associated with the highest sub-trip emissions, capturing these conditions is considered a step forward towards more accurate emission estimation.

The use of the micro-trip as the unit to average speed and EFs over is also a conceptual advancement of current practice as this approach naturally matches traffic network data which yields low average speeds for short road segments as opposed to high average speeds on longer segments where start stop driving is less frequent. Unlike traditional methods which tend to average EFs over longer and theoretically undefined trips, the use of the micro-trip approach significantly reduces the scatter in the underlying data (data underlying the current approach is highly scattered e.g. Figure 37), making the whole premise of fitting a function to this data more sensible as a relation between speed and EFs becomes apparent. Also, considering that 38%

of all simulated road links in Bradford were ≤ 100 m (Chapter 3), the micro-trip approach is a better representation of this urban road network's characteristics.

Another strength of the current approach is its transparency and transferability to other contexts and cities, given that the testing kit and emission modelling software PHEM can be made available. In contrast, there is lack of clarity about how COPERT average-speed-emission functions are developed including an unclear definition of 'trips' and driving cycles used to generate the model's underlying data, and no reporting of goodness of fit or errors in the fitted functions.

Finally, the collection of real-world speed profile data by tracking vehicles as was done in this work, is significantly cheaper and quicker than measuring vehicle emission measurements either in the laboratory or with PEMS and remote sensing instruments in the real-world, making this approach a relatively practical method for deriving EFs for a wide range of vehicle types and classes in a specific study area.

4.5.3. Limitations

Despite its strengths, the approach also has its limitations. The key limitation is that the new average-speed-emission functions are based on model estimates, partly derived from the observed instantaneous speeds, rather than independent exhaust emission measurements. Although this is a key limitation as the new emission model/average-speed-emission functions are based on another model's (PHEM) estimates, this is currently the only feasible way to derive new average-speed-emission functions for the wide range of vehicle classes operating on the Bradford network. It is practically impossible to comprehensively measure exhaust emissions from all vehicle classes operating in Bradford under real-world driving conditions, due to high costs associated with emission measurement equipment and campaigns, the long durations needed to comprehensively capture a representative traffic fleet and the impracticality of recording emission levels from current and previous vehicle classes/models on the roads for the years concerned. There is also a lack of observed vehicle emission datasets that could arguably be used to develop models tailored to the study area, e.g. a synthesized set of emission measurements for all vehicle types over the Bradford speed profile is lacking. However, given that the main aim was to develop useful average-speed-emission functions which can capture the under estimated emissions in urban driving, the current approach is an effective and a practical approach and the issues above are beyond the direct scope of this study.

Further, the PHEM model has been validated, specifically in work undertaken within the author's research group (Tate, 2015b, Wyatt et al., 2014), and this allows to confidently estimate the second-by-second emissions of all vehicle types and subcategories for a real-world driving cycle. In fact, the COPERT model blends instantaneous measurements and PHEM modelled data in its' underlying database, from which it derives average-speed-emission functions. Emission estimates from the new functions, however, need to be validated against real-world data, when available.

PHEM estimates, as with any other emission model's estimates, have only been partially validated, as true vehicle emissions are unknown and are practically impossible to measure for all vehicle classes operating in the area and time period concerned (Smit et al., 2010). Overall, this partial validation supports the use of PHEM for certain vehicle classes such as diesel passenger cars, buses and HDVs. It was, however, shown that PHEM may under estimate NO_x emissions at speeds lower than 40km/h and that its estimates are less reliable for higher powered and heavier vehicle (e.g. SUV BMW X5, BMW M3), but this latter point is less relevant for the present research study as 'average' vehicle specifications were used for the modelling. As mentioned before, PHEM attempts to replicate the emission performance of an average vehicle in a sub-category, rather than representing one specific model or the variability in performance of vehicles under a sub-category. In the case of petrol vehicles, the model's estimates were shown to be least accurate, and PHEM can over- or under estimate instantaneous vehicle emissions. The reasons behind these inaccuracies are uncertain, but the very low absolute values of NO_x emissions from petrol vehicles make it hard to accurately measure and model and causes an increased uncertainty in these emission estimates. This should be taken into consideration when contrasting measured and modelled values from petrol vehicles. Compared to diesel vehicles, petrol vehicles' NO_x (e.g. passenger cars and LDVs) can be an order of magnitude lower, making the contribution of petrol NO_x to the overall emission inventories less significant.

Other limitations include that the data available for curve fitting was substantial in the cases of speeds less than 50 km/h but very limited for speeds above 50 km/h (8 points, see Figure 50). This was because the focus of this study was on the urban road network in Bradford and therefore most roads surveyed were not motorways where average vehicle speeds are expected to be higher. The limited number of average speed and EF pairs at speeds above 50 km/h may have caused the curves to under estimate EFs at the higher speeds as there were no data points to leverage the curves at those ends, as would be expected (O'Driscoll et al., 2016). The driving cycles used in this work were assumed to have captured the representative distribution of vehicles speeds, acceleration and engine power demand over the road network in Bradford. There are, however, certain roads in Bradford which have not been surveyed and the survey time was limited (30.5 hours). Although it is unlikely that the speed profile on roads which were not surveyed significantly differs from the ones surveyed in this study, this may be the case and warrants further exploration.

Also, 'average' vehicle parameters, which were used for modelling the different vehicle classes in this study, can conceal the high level of variability in real-world fleets and do not reflect operational conditions of the vehicles including effects of the vehicle's age, malfunctions, deterioration, maintenance conditions, tampering and fuel quality or use of alternative fuels (Rhys-Tyler, 2017, Chen and Borken-Kleefeld, 2016). As there was no information available for the vehicle specifications in Bradford, average vehicle specifications were sourced from available Automatic Number Plate Recognition surveys in Leeds (for passenger cars and LDVs), and London (for buses, coaches and HDVs), and this approach is not ideal as the traffic fleet in those areas might differ from Bradford.

The impact of road gradient on emissions was not considered in the present work, due to time and resources constraints and the fact that the geometry of the traffic road network was of insufficient detail i.e. nodes were not correctly geo-referenced and road links were represented as straight lines. However, in previous work of the author (Khreis, 2016), NO_x emissions were modelled in PHEM in two scenarios: the first assuming that the Bradford test area is flat and the second incorporating road grade data as measured at 1 Hz by the instrumented survey vehicle (using a accelerometer). The new average-speed-emission functions fitted to the data were of high goodness of fit in most cases but the key trend apparent was that including road grade in the model estimates highly increased the scatter in the EFs data and therefore decreased the goodness of fit for the fitted functions. This result is reasonable as road grade adds another dimension of variability to the EF estimates, which is not being initially accounted for by the fitted functions that only rely on average speed as the sole explanatory variable of emissions. The inclusion of road gradient also increased the average EFs across all passenger car classes by up to 3.8% and substantially widened the range of the emissions. These findings highlight the potential errors in emission estimation when road grade is not considered.

Finally, although the micro-trip analysis approach has the potential to be more informative and naturally matches the characteristics of the urban road network, the analysis is more labour intensive and the reduction of uncertainties in model estimates remain unknown as there have been no studies adopting this approach in emission modelling before and validating it. More work needs to be done to elaborate the potential advantages of this approach.

4.5.4. Avenues for Future Work and Next Step

The spatial and temporal coverage of the vehicle tracking surveys can be expanded in future work and some of the potentially important routes that can be covered include Halifax Road (south-west) and Great Horton Road (west-south). The surveys should cover more road sections with higher average speeds (>50 km/h) to contribute to more data points at those segments. Future work would benefit from validating EFs derived from the new average-speed-emission functions, using PEMS or remote sensing data. The impact the age of the fleet and quality of fuel used could be further explored when more data on the fleet characteristics become available. Future applications of PHEM would benefit from improvements in petrol emissions measurement and modelling. The impact of road gradient on emissions was not accounted for in this study and new average-speed-emission functions could be developed for specific gradient increments, which would be useful with the development of correctly geo-referenced traffic models. The use of traffic microscopic model packages such as AIMSUN or VISSIM which can output second-by-second vehicle traces can be used as inputs to new micro-trip-based average-speed-emission functions and can provide emissions information like that achieved using PEMS methodologies. Finally, as true big data collection methodologies including vehicle telematics are rapidly gaining traction, it will soon be possible to apply the new average-speed-emission functions to a larger and more detailed traffic network and fleet data, potentially at the street and the minute level.

Currently, it is possible to link the new average-speed-emission functions to mesoscopic traffic models such as SATURN (Chapter 3), and subsequently to dispersion models. The next steps of this thesis will knit together these multiple and novel data sources and models for health impact assessment. The SATURN traffic flows and average traffic speeds will be used as inputs to the newly developed functions to estimate a Bradford road transport NO_x emission inventory for 2009. The same will be repeated using standard average-speed-emission functions sourced from COPERT and differences will be explored in Chapter 5.

5 Vehicle Exhaust Emission and Traffic Linkage and Dispersion Modelling

5.1. Background

5.1.1. Dispersion Modelling

Air pollutant concentrations, and therefore human exposure to air pollution, can be assessed using several methods/models; one of which is dispersion modelling (Chapter 2). Dispersion modelling is the mathematical simulation of the dispersion of selected air pollutants in ambient air. The simulation involves the construction of a dynamic model (i.e. changes over time), which uses information on traffic flows and other emission sources, emission rates, meteorology, atmospheric boundary layer conditions and atmospheric chemistry to simulate atmospheric dispersion processes (Briggs et al., 1997, Health Effects Institute, 2010). The results are estimates of ambient concentrations of selected air pollutants.

Dispersion models can estimate air pollution concentrations for different scales ranging from regional (100-1000 km) to micro (10-100 m) (Health Effects Institute, 2010). The model outputs can be in the form of episodic short-term and/or long-term exposures at receptor points and/or grids of interest (Carruthers et al., 1994). Most dispersion models/packages rely on Gaussian plume equations to estimate ambient pollution concentrations (Holmes and Morawska, 2006). Gaussian plume models are often used as they offer an efficient compromise between reasonable accuracy and manageable computational time (Briant et al., 2013). Gaussian plume models are based on vertical and horizontal Gaussian plume distributions (Figure 52). The air pollution concentration at any given position (c) is calculated as in Equation 5.1 which describes a mixing process that results in a Gaussian concentration distribution:

$$c(x, y, z) = \frac{Q}{2\pi\sigma_y\sigma_z u} \exp\left(\frac{-y^2}{2{\sigma_y}^2}\right)\left(\exp\left(\frac{-(z-h)^2}{2{\sigma_z}^2}\right) + \exp\left(\frac{-(z+h)^2}{2{\sigma_z}^2}\right)\right) \ldots \text{(Equation 5.1.)}$$

Where Q is the source term; x is the downwind; y is the crosswind; z is the vertical direction; u is the wind speed at the h height of the release; σ_y, σ_z deviations which describe the crosswind and vertical mixing of the pollutant and are determined by stability class or travel time from the source.

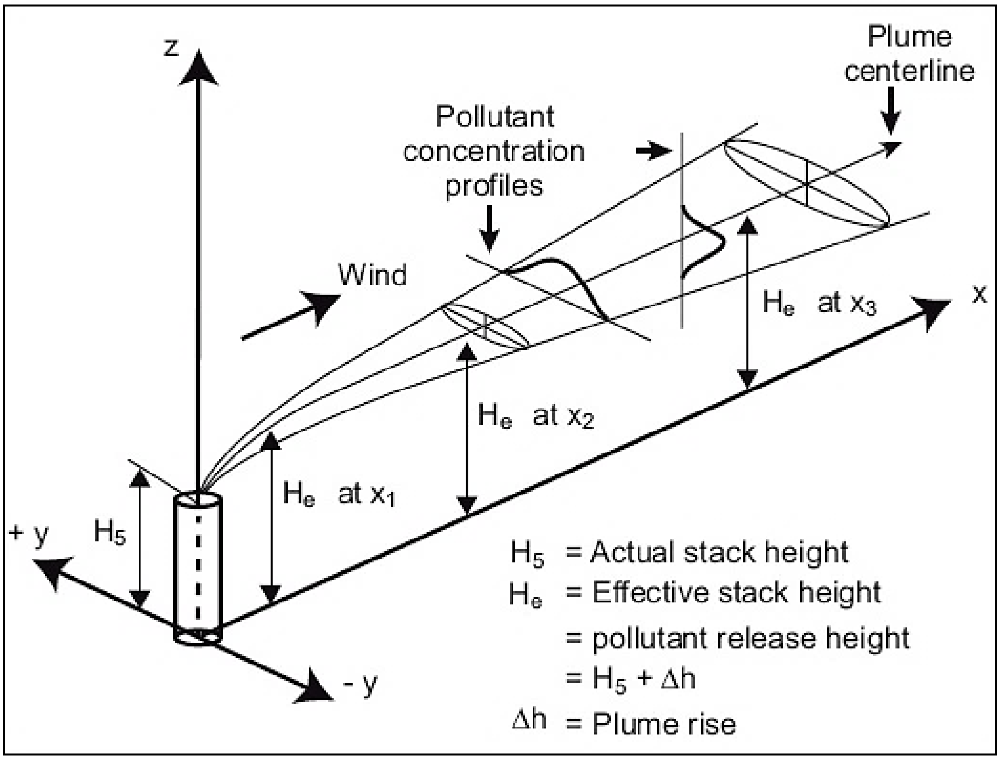


Figure 52 Schematic of the Gaussian Plume from a Point Source, Source: Schultz (1991)

Gaussian plume models assume steady-state conditions; that there are no chemical or removal processes taking place and that there are no interactions between the plumes which can be significant within urban environments (Vardoulakis et al., 2003, Holmes and Morawska, 2006). They further have limited capacity to take into account recirculation effects caused by multiple buildings or at intersections (Holmes and Morawska, 2006). In the case of line sources, e.g. roads, the source is divided into elementary/smaller line sources, each of which is treated as a point source. The point sources solution over the line are integrated so as to sum the contributions of each elementary source forming the contribution of a finite line source (Briant et al., 2013).

In comparison to the other air pollution/exposure models used in asthma and TRAP research (Chapter 2), dispersion models were considered superior as they can offer the highest temporal and spatial resolution possible; take into account the compounded effects of proximity to multiple roads on exposures; give information on specific pollutants and are most specific to traffic sources as the contribution of TRAP to the overall exposures can be explicitly quantified (Khreis and Nieuwenhuijsen, 2017). Their key disadvantages are in their severe data, software and expertise demands and the uncertainties associated with their assumptions (e.g. Gaussian plume models: see above) and their emission inputs including 1) vehicle emission estimates and 2) emission estimates of other sources such as domestic heating, factories and regional air pollution; all of which lead to uncertainties in resulting air pollution estimates (Barrat, 2013, Jerrett et al., 2005, Sayegh et al., 2016). As demonstrated in Chapter 4, vehicle emission factors and, consequently, vehicle emission estimates are a particular source of uncertainty in air pollution modelling. A formal quantification of the impacts that vehicle emission factors have on dispersion models' estimates is largely missing.

In TRAP-associated health effects and impacts assessment studies, dispersion models have not been used often (e.g. see Chapter 2 and Nieuwenhuijsen et al. (2017)), partly due to the substantial amount of data required (e.g. traffic, emissions and meteorology); the need for specialized software (e.g. GIS, dispersion software, and integrated software); hardware capable of processing these data and trained personnel (Health Effects Institute, 2010). Further and to the best of the author's knowledge, there have not been any previous attempts to alter emission factor inputs and assess the air quality and health impacts associated with dispersion model estimates based on different emission inputs. This is a significant knowledge gap as errors in the emission assessment stage can propagate through the whole chain of modelling and impact trends, results and subsequent policy advice (Figure 1).

This work will contribute to improved understanding of the effects of emission factors on 1) dispersion modelling results (their validity) and 2) quantified health impacts (their magnitude). Further, this work adds to the literature by exploring agreement and differences between dispersion modelling results and results from commonly used exposure assessment models, namely the LUR models (Dijkema et al., 2011).

5.1.2. Dispersion Modelling using ADMS-Urban

One of the most commonly used dispersion modelling packages in the UK is the Atmospheric Dispersion Modelling System; referred to as ADMS, with ADMS-Urban being its most comprehensive and up-to-date version (Cambridge Environmental Research Consultants Ltd, 2013). ADMS-Urban is a PC-based model, which simulates the atmospheric dispersion of pollutant emissions from traffic, industrial and domestic sources, within urban areas. Cambridge Environmental Research Consultants first developed the system in the UK in 1990. Currently over eighty local authorities, including Bradford Metropolitan District Council, use ADMS-Urban for their Review and Assessment of air quality and to develop air pollution action plans and corrective strategies when needed (Cambridge Environmental Research Consultants Ltd, 2013). ADMS-Urban is also a recognized tool under the UK National Air Quality Strategy process; which further supports its use.

The ADMS-Urban model uses a Gaussian plume distribution to calculate pollutant concentrations except in the case of vertical distribution under convective/unstable atmosphere conditions where the model employs a skewed Gaussian distribution (Cambridge Environmental Research Consultants Ltd, 2014). The framework of the ADMS-Urban model including its key inputs, processes/modelling options and outputs is shown in Figure 53 and described in full in the software's manual (Cambridge Environmental Research Consultants Ltd, 2014). Briefly, the inputs required are 1) source parameters of the included sources (e.g. road, industrial and grid sources); 2) time varying emissions to account for e.g. diurnal changes in traffic flows and, consequently, emissions; 3) meteorological data including site data (surface roughness and latitude), wind speed, wind direction, cloud cover; 4) background concentrations of the modelled pollutants and 5) locations of receptor points or grids. The outputs generated could be 1) short-term air pollution concentrations (over an hour or 15 minutes) and 2) long-term air pollution concentrations represented as annual averages, percentiles or exceedances.

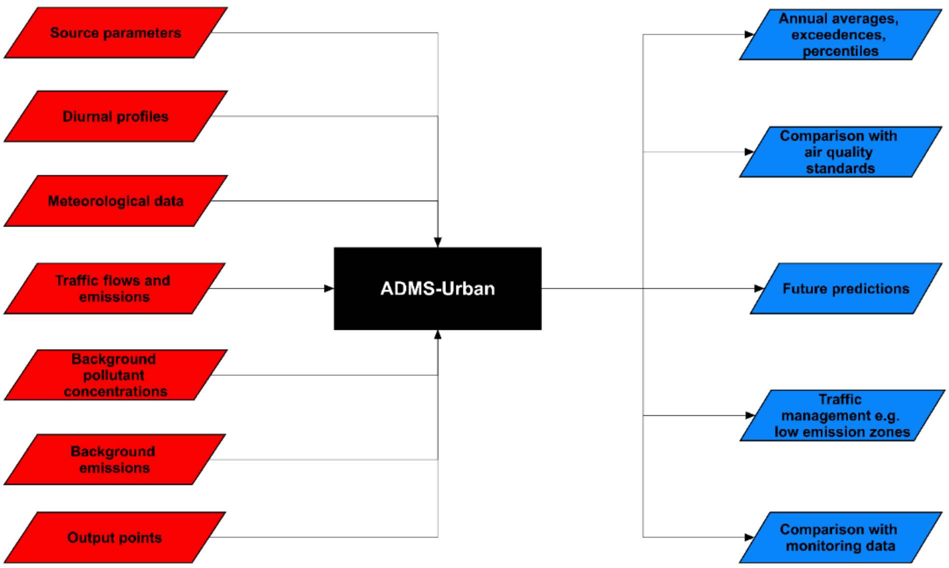


Figure 53 Inputs and outputs of ADMS-Urban, Source: Modified after Cambridge Environmental Research Consultants Ltd (2014)

5.1.3. ADMS-Urban Validation

Previous validation of the ADMS-Urban model showed good agreement with measured data (Department for Environmental Food and Rural Affairs, 2010). However, at the roadside, ADMS-Urban generally tends to under estimate TRAP concentrations; a problem that was '*undoubtedly*' attributed to the unrealistically low vehicle emission factors (Williams et al., 2011). Indeed, a literature review conducted here identified a few studies that validated the ADMS-Urban model and, overall, showed that the model tends to under estimate pollution levels, as compared to measurements. This literature is summarized in Table 20; discussed next and overall highlights the need for improved vehicle emission estimates that can reflect the higher emission levels measured in real-world conditions (Chapter 4).

In a summer campaign of 62 sites in Paris, Briant et al. (2013) measured a monthly mean value of 22.5 µg/m^3 NO_2 compared to a 9.6 µg/m^3 NO_2 as modelled by ADMS-Urban. In the winter campaign, at the same sites, the authors measured a monthly mean value of 35.15 µg/m^3 NO_2 compared to a 19.4 µg/m^3 NO_2 as modelled by ADMS-Urban, showing that the model tends to under estimate air pollution concentrations, as measured by passive diffusion tubes. Emission factors used in the model were sourced from COPERT 3. In another exercise, Peace et al. (2004), using the latest UK emission factors at the time (sourced from TRL/DfT functions), set up and validated an ADMS-Urban model for Greater Manchester. The validation was undertaken at 12 continuous fixed-site monitoring stations available. Ten of these stations were classified as urban background, 1 as roadside and 1 as sub-urban station. The results of the validation showed that the model under estimated NO_x and NO_2 concentrations, at all sites but the sub-urban site. The R^2 of the model was not reported in the paper but was calculated and equalled 88%. Dėdelė and Miškinytė (2015a) used ADMS-Urban to model NO_2 concentrations in Kaunas city and validated the modelled concentrations against measurements from 41 Ogawa passives samplers operated as part of the ESCAPE project. Emission factors used were sourced from the DMRB emission factor dataset, built in the dispersion model, but the vehicle fleet was assigned an average age of 14 years and a large number of cars on the road were selected to not be equipped with a catalytic converter. Overall, the ADMS-Urban estimates were higher than the average measured NO_2. However, the model tended to under estimate the maximum concentrations and overestimate the minimum concentrations. In their follow-up study, Dėdelė and Miškinytė (2015b) compared modelled NO_2 concentrations with four continuous air quality monitoring stations in Kaunas city. At the two traffic stations and the background station, modelled average concentration of NO_2 was lower than the observed, whilst the opposite trend was seen at the residential site. In an air quality assessment exercise for London, Carruthers et al. (2003) set up and validated ADMS-Urban against measurements of NO_x and NO_2 from 24 fixed-site monitoring stations. The authors showed that the model generally tends to under estimate annual average NO_x and to a lesser extent NO_2 concentrations, especially at the roadside. For example, measured versus modelled annual average NO_x at the 10 roadside stations was 115 ppb and 99 ppb, respectively. Measured versus modelled annual average NO_2 at the 10 roadside stations was 35 ppb and 33 ppb, respectively. The variation at the individual sites was greater. Finally, in a wider validation study, de Hoogh et al. (2014) used and validated 13 dispersion models for 13 European study areas. At 3 of these areas; Bradford, London and Barcelona, an ADMS-Urban model was used and was validated against 40, 27 and 40 ESCAPE monitoring sites for NO_2, respectively. de Hoogh et al. (2014) found that the median concentrations were under estimated. On average, the measured and modelled NO_2 concentrations correlated well with a median Pearson correlation coefficient of 0.74, 0.85 and 0.75, for Bradford, London and Barcelona, respectively (de Hoogh et al., 2014).

5.2. Chapter Objectives and Contribution to Literature

The first objective of this research phase was ***to link the traffic activity estimates (Chapter 3) to the standard and the newly developed average-speed-emission functions (Chapter 4) and calculate the Bradford road transport NO_x emission inventory for year 2009; using the two different emission models and exploring the differences.*** The second objective of this research phase was to ***set up, run and validate two ADMS-Urban dispersion models using emission rates as calculated from the two different emission models and explore the differences.*** The third objective of this research phase was to ***compare the outputs and validation metrics of the dispersion models to the performance of the ESCAPE LUR models in Bradford***. As such, this research phase contributed to the absent knowledge available on the impact of emission factors on local emission inventories, TRAP and subsequent childhood population exposure and associated health outcomes. It also tested and validated two-novel full-chain exposure assessment models developed in this research study and compared them to a commonly used method in exposure assessment.

Table 20 ADMS-Urban Validation Studies

Study	Setting	Vehicle emission factors used	Validation dataset	R^2	Validation conclusion
Briant et al. (2013)	Paris region, France	COPERT 3	62 NO_2 passive diffusion tubes	73%	Model *under* estimates
Peace et al. (2004)	Greater Manchester, UK	TRL/DfT functions	NO_x and NO_2 at 12 continuous fixed-site monitoring stations	88%	Model *under* estimates, particularly at the roadside site
Dėdelė and Miškinytė (2015a)	Kaunas city, Lithuania	Design Manual for Roads and Bridges (DMRB 1999)	40 NO_2 Ogawa passives samplers	73% - 79% (depending on season)	Model *over* estimates
Dėdelė and Miškinytė (2015b)	Kaunas city, Lithuania	Design Manual for Roads and Bridges (DMRB 1999)	NO_2 at 4 continuous fixed-site monitoring stations	56% -91% (depending on site type)	Model *under* estimates, except at the residential site
Carruthers et al. (2003)	London, UK	NA (likely COPERT)	NO_x and NO_2 at 24 continuous fixed-site monitoring stations	67%	Model *under* estimates, particularly at the roadside site
de Hoogh et al. (2014)	Bradford, UK; London, UK; Barcelona, Spain	DMRB 1999 for Bradford, NA for others (likely COPERT)	40, 27 and 40 NO_2 Ogawa passives samplers	55%, 72% and 57%	Model *under* estimates

5.3. Methods

5.3.1. Linkage of Traffic and Average-Speed-Emission Functions

All standard average-speed-emission functions sourced from the COPERT 4 v10.0 spreadsheets and all newly developed PHEM-based average-speed-emission functions were coded onto an Excel spreadsheet. In this spreadsheet, the user needs to enter the average traffic speed (km/h) for the NO_x emission factors (g/km) to be calculated using the two emission models (see Section 4.3.9). The user also needs to specify the overall traffic flow (vehicles/h) at the link level; for the traffic fleet-mix to be calculated (vehicle classes, EURO emission standards, after-treatment technologies and weight categories where applicable) (see Section 3.4.1).

For each vehicle type in the traffic fleet, the calculated NO_x emission factor (g/km), from the two emission models, is then multiplied by the link's length in km and the number of vehicles for that vehicle type. The result is NO_x emissions in g, at each road link, for each vehicle type; using the two different emission models. The sum of the NO_x emissions across all vehicle types over each link is the total link-based NO_x in g. The sum of the NO_x emissions across all the links is the total road network NO_x in g; attributable to road traffic.

This process is illustrated in Figure 54 and was undertaken 48 times corresponding to the 24 hours in an average weekday and the 24 hours in an average weekend; using the weekday and weekend hourly traffic flows previously estimated in Chapter 3 (see Section 3.4.5). The scaling of the traffic flows across the 24 hours (described in detail in Chapter 3) is an addition to common practice which either assumes that the traffic is constant (de Hoogh et al., 2014); or uses inter-peak traffic flows to fill all hours outside the simulation period (City of Bradford Metropolitan District Council, 2013). The AM, inter-peak and PM peak speeds, as estimated by the SATURN model (Chapter 3), were directly used to calculate emissions at those hours. For all other hours (for which no speeds existed), the inter-peak speed was used.

5.3.2. Compilation and Comparison of Emission Inventories

For each vehicle class/EURO emission standard/after-treatment technologies/weight category (e.g. for a rigid HDV, EURO 5 SCR, 7.5 tonnes), total NO_x emissions were calculated by summing NO_x emissions across all links constituting the road network. The calculations were undertaken twice using the standard COPERT and the new PHEM-based average-speed-emission functions. The results from the two emission models were compared, both in terms of 1) absolute magnitude and 2) percentage of the total road network NO_x attributable to each vehicle type (i.e. source apportionment). The results for an average weekday are presented in Section 5.4.1.

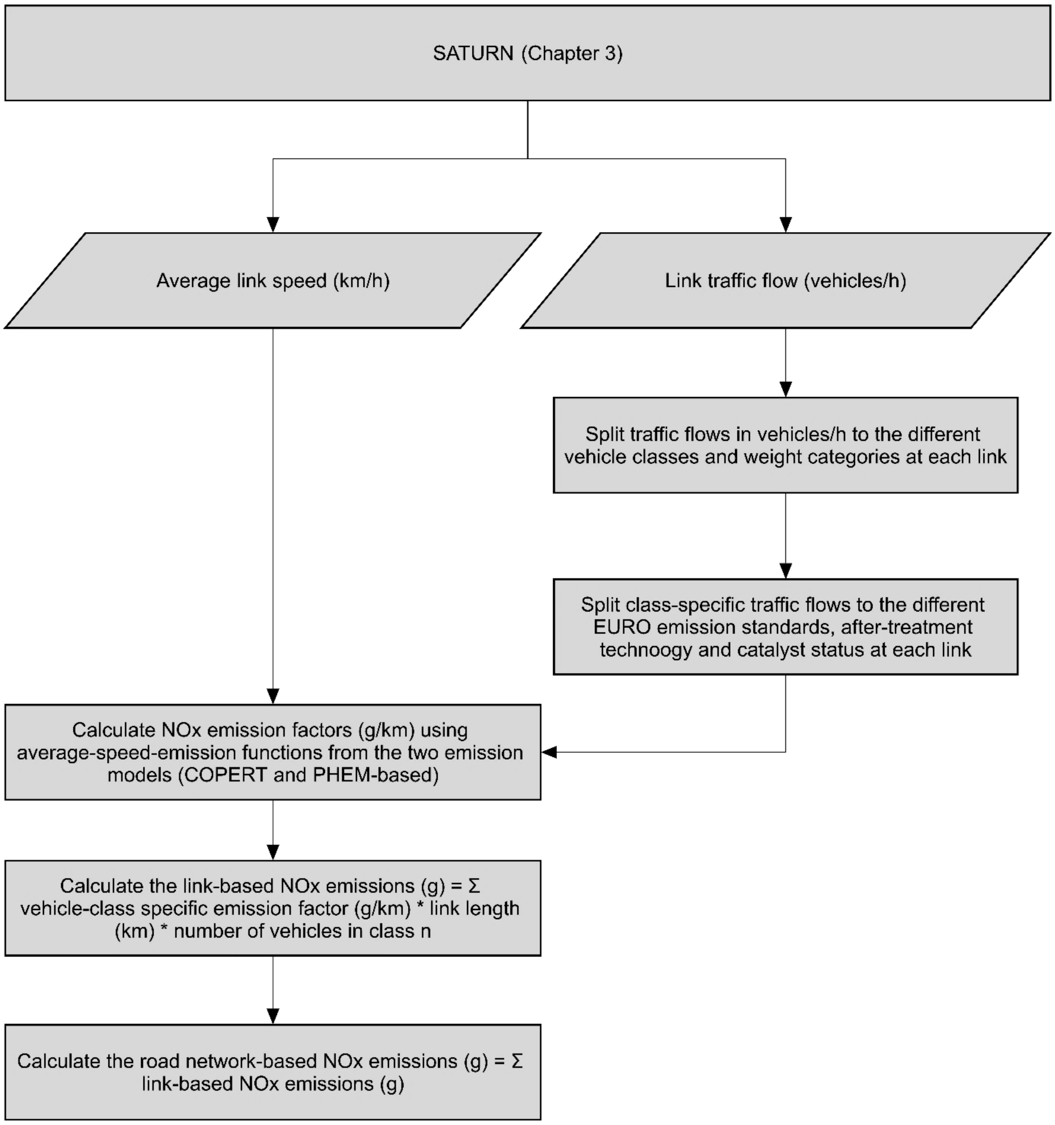


Figure 54 Traffic and Average-Speed-Emission Functions Linkage and Road Network NO_x Emissions Estimation Methodology, Source: Own Work (NCH Software)

5.3.3. Compilation of Input Data for of ADMS-Urban

A. Site and Meteorological Data

The ADMS-Urban model requires input data about the modelling site and meteorological conditions. The data entered is documented in Table 21 and compared to the default values of the model; which were sometimes altered (Cambridge Environmental Research Consultants Ltd, 2010). The meteorological data was entered through a prepared meteorological data file including the following parameters in a series of hourly sequential data covering year 2009:

- ‘YEAR’: the year
- ‘TDAY’: the Julian day number

- 'THOUR': time of data
- 'T0C': temperature in C°
- 'U': wind speed in m/s
- 'PHI': wind direction in degrees°
- 'P': precipitation rate in mm/h
- 'CL': cloud cover in oktas
- 'RHUM': relative humidity in percent

This data is used in the model to calculate the boundary layer height and other parameters used in the dispersion simulations (Cambridge Environmental Research Consultants Ltd, 2010). The meteorological data was obtained from the Bingley Samos weather station (metoffice.gov.uk, ND) which was 9.7 km of the city centre (Bradford's City Hall) and had the following coordinates: 53°48'39.6"N 1°51'54.0"W. To verify this weather station's readings, this data was aggregated and compared to annual data published on-line by the commercial company Weather Underground (https://www.wunderground.com/). No anomalies were detected. A further inspection of the location of the meteorological site revealed that the site was in an open and a less built-up area than the dispersion site (i.e. the Bradford metropolitan area). Therefore, the meteorological site was considered 'Parkland, open suburbia', rather than the (default) 'Large urban area' categorization selected for the dispersion site. Due to the presence of buildings, the wind speed is expected to decrease in large urban areas when compared to parkland or open suburbia (e.g. rural locations). This effect was, therefore, taken into account by using different categorizations and surface roughnesses for the dispersion versus the meteorological site (Stocker, 2015).

Table 21 Site and Meteorological Conditions entered in ADMS-Urban

Site data	Input (default value)	Rationale and description, where applicable
Latitude	53.8° (52°)	Latitude and longitude coordinates for Bradford, United Kingdom in Decimal are 53.79391, -1.75206

Dispersion site – surface roughness (m)	1.5 (0.5, 'Parkland, open suburbia)	Surface roughness at the dispersion site (in meters) is based on land use and corresponding values for different land use types are given in the model. The value 1.5 corresponds to 'Large urban areas', which was considered most appropriate
Dispersion site – use advanced option?	Checked and following data entered – surface albedo = 0.23 (0.23), Priestley-Taylor parameter = 1 (1), minimum Monin-Obukhov length (m) = 30 (30) were defined	Surface albedo = 0.23 (the ground is not snow covered), Priestley-Taylor parameter = 1 (moist grassland), Minimum Monin-Obukhov length (m) = 30 (cities and large towns), Precipitation = Same as met. Site
Met. measurement site – surface roughness (m)	0.5 (Use dispersion site value)	The meteorological measurement site characteristics were considered different from those at the dispersion site as the meteorological measurement site was in the urban area of Bradford but in an open and less built-up area. The value 0.5 corresponds to 'Parkland, open suburbia', which was considered most appropriate
Meteorological data	Input (default value)	Rationale and description, where applicable
Met. Data	From file	A comma-separated file with a. *met* extension containing a series of hourly sequential data covering year 2009. Missing data were identified using the value '-999'. A total of 779 hours was the maximum missing number of hours (for the CL parameter) in the year 2009 (9% of the data)
Height of recorded wind (m)	10 (10)	Default value selected, no other specific data was available
Met. data in sectors of (degrees)	Checked – 10 (10)	Wind direction measurements were reported to the nearest 10 degrees (i.e. wind data are in 10-degree sectors)
Met. Data are hourly sequential	Checked	The meteorological data was a series of hourly sequential data covering year 2009

B. Background Air Quality Data

NO_x air pollution background data was also needed in the dispersion modelling to account for the NO_x contirbution of air pollution sources other than traffic. Multiple sources of background air pollution data were considered, including:

- A site in Bingley, which was classified by CBMDC as a background station (City of Bradford Metropolitan District Council, 2010), but had a high annual NO_x mean of 81 µg/m^3 and hence was excluded;

- 24 urban background ESCAPE sites which had an average annual NO_x of 38.4 µg/m^3 (Table 23); and
- Background air pollution maps from DEFRA which give spatially varying annual NO_x concentrations at 1km x 1km grids covering sources like industry, rail, domestic, aircraft emissions, regional rural concentrations (Department for Environment Food and Rural Affairs, 2016a).

Model's validation indicated that using the spatially varying background concentrations from DEFRA's map rather the constant concentration from the ESCAPE's diffusion tubes resulted in better model performance (Table 28). As such, and because spatially varying background concentrations were considered more realistic, the DEFRA background map was used in final analyses.

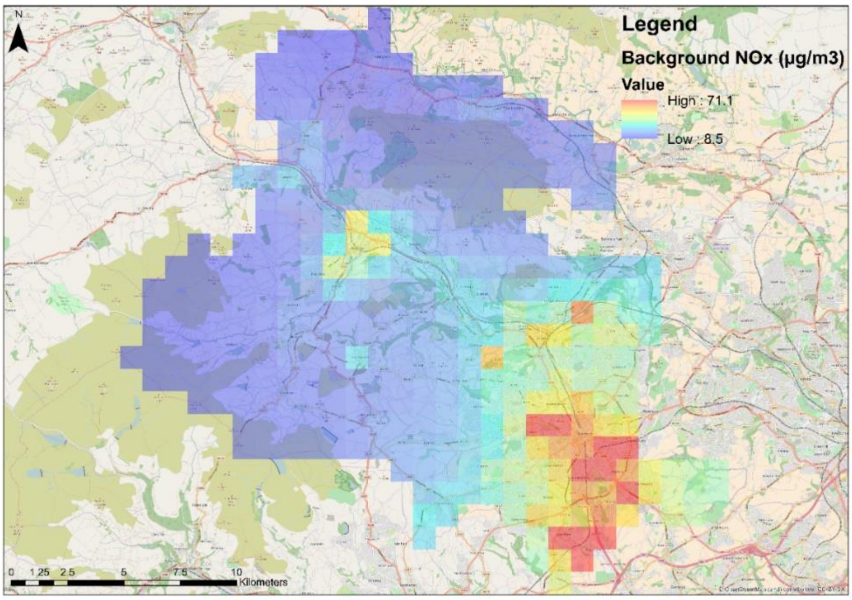


Figure 55 Annual (2010) NO_x Background Map, Source: Own Work (Arc Map 10.4), Data Source: Department for Environment Food and Rural Affairs (2016a)

The varying NO_x background concentrations ranged from about 8.5 to 71 (mean = 14.73) µg/m^3, based on the grid's location. The underlying modelling suite meets the requirements for uncertainty specified in the European Air Quality Directives (Department for Environment Food and Rural Affairs, N.D.). The background concentrations originated from the following sources: industry, domestic, aircraft, rail, point sources, rural sources and "others", as decribed in more detail in Department for Environment Food and Rural Affairs (2016a) and as summarized in Table 44, Annex 5.1.

In the main analysis, all the traffic sources were excluded from the final NO_x background concentrations used, to avoid any double counting of TRAP. The only TRAP component that was included on top of the NO_x background concentrations was that estimated by ADMS-Urban. The traffic sources excluded are shown in Table 44 and are motorways, trunk A roads, primary A roads and minor roads and cold starts. The exclusion of minor roads and cold starts, however, may result in a worse performance of the ADMS-Urban model as these sources were not explicitly included in the SATURN traffic network, which was focused on main and strategic roads. As such, an additional sensitivity analysis explored the impact of adding minor road and cold start concentrations to the ADMS-Urban models' estimates (Table 44).

C. Road Emission Sources Data

4,500 road sources and their NO_x emission rates defined in g/km/s were used in the dispersion modelling. Road source emission rates were entered directly into the model and were *not* calculated from traffic flow data and the model's in-built database of traffic emission factors; as regularly practiced (de Hoogh et al., 2014, City of Bradford Metropolitan District Council, 2013). This bypassed the in-built emission models/average-speed-emission functions and was done to enable a full and exhaustive comparison of the impact of emission factors on the final modelling outputs (air quality and subsequently health impacts). Also, the traffic flow categorization permitted within ADMS-Urban was restricted to a maximum of 6 vehicle categories: passenger car < 3.5 t; London taxi/Hackney carriage < 3.5 t; LDVs < 3.5 t; motorcycles/moped < 3.5 t; HDVs ≥ 3.5 t; and buses/coaches ≥ 3.5 t. This was a much less detailed description of the traffic fleet than constructed in the present study which modelled 167 vehicles classes instead (Section 3.4.1.). The emission rate in g/km/s from each road/link was calculated as the product of the emission factor in g/km for each vehicle class on the link (at that specific link's speed), the number of vehicles/hour for each vehicle class on the link, summed across all vehicle classes on each link and multiplied by a time conversion factor (Equation 5.2):

$$\text{Road link emission rate}\left(\frac{\frac{\text{g}}{\text{km}}}{\text{s}}\right) = \sum(\text{vehicle class specific emission factor at link speed (g/km)} * \text{number of vehicles in each class}) * \left(\frac{1\text{ hour}}{3600\text{ seconds}}\right) \ldots \text{(Equation 5.2.)}$$

This process was undertaken twice using emission factors from COPERT and from the newly developed PHEM-based average-speed-emission functions. It was also undertaken for the 24 daily hours in both the weekdays and the weekend (this data was used to develop time varying emission factors; described next). Thus, at each road link, and in each hour of the day, an emission rate was calculated.

As only 1 dataset of road sources emissions can be entered in ADMS-Urban (i.e. it is not possible to enter the 24-hour emissions datasets to be modelled), the AM peak hour was the one selected to be directly used in the model's run. A Microsoft Access database, in ADMS-Urban Emission Inventory format (Cambridge Environmental Research Consultants Ltd, 2010), was prepared as an input file. The Emission Inventory contained the AM emission rates; other road characteristics including source names; road widths (an average of 17 m (de Hoogh et al., 2014)) and geographical locations of the start and end of each road link.

The maximum number of road sources possible to model in one ADMS-Urban (version 3.0.0.) run was 3000 (Cambridge Environmental Research Consultants Ltd, 2010). Therefore, road links and their emissions had to be split in smaller input files and runs (as described in 5.4.4.); the concentration results of which at the same set of output points were summed up at the end of the modelling. This was considered an acceptable practice in this study where chemistry was not modelled and the same set of output points were used in every run. Further, this was checked by running 1500 roads at once and then splitting them into 3 input files of 500 roads each, the NO_x sum of which was equal to the results of the bigger run.

D. Time Varying Emission Factors

Unless otherwise specified, the emissions rates in ADMS-Urban are assumed to be constant across all hours of the day; based on the hour that has been input in the model. As such the effect of the traffic, and therefore the emissions, diurnal variations are disregarded. This is likely to impact the final estimated air pollution and exposure levels and therefore the associated health impacts. To compensate for this, an additional modelling option specifying time varying emission factors was used to enable modelling NO_x concentrations from vehicle emissions that vary by hour of the day. The 'time varying emission factors' option within the model was checked and a single set of hourly time varying emission factors, for each hour in a weekday and a weekend, were specified. The hourly time varying emission factors also (slightly) differed based on the emission model used: COPERT or the newly developed PHEM-based average-speed-emission functions (Figure 56). These factors needed to be entered manually, for each model run, as no automatic import option existed.

The time varying emission factors were calculated as follows. At each individual link, traffic flows across all weekday and weekend hours were estimated either using the SATURN outputs, or, where not modelled, using the ATC data as detailed in Section 3.4.5. At each hour of the weekday and the weekend and at each link, the link's emission rates (g/km/s) were calculated by linking the hour's traffic flow at that link with the COPERT and the PHEM-based average-speed-emission functions (Section 5.3.1.) and then applying Equation 5.2. At each hour, a ratio between each link's emission rate and that link's emission rate in the AM peak hour was calculated and considered as the time varying emission factor for that specific link. The median value of the time varying emission factors across all links, at each hour, was selected as the time varying emission factor of that hour (Figure 56). The median value was selected instead of the average value as the distribution of time varying emission factors was skewed to the right and an average value, being highly susceptible to the influence of high outliers, did not result in standard reasonable traffic trends (e.g. Figure 33 and Figure 34). Conversely, the use of the median value allowed replicating standard traffic diurnal profiles (Figure 33 and Figure 34). During the simulation, the ADMS-Urban model used the time varying emission factors shown in Figure 56 to multiply the AM hour emission rates for each road (the only input) by the appropriate factor specified for each hour.

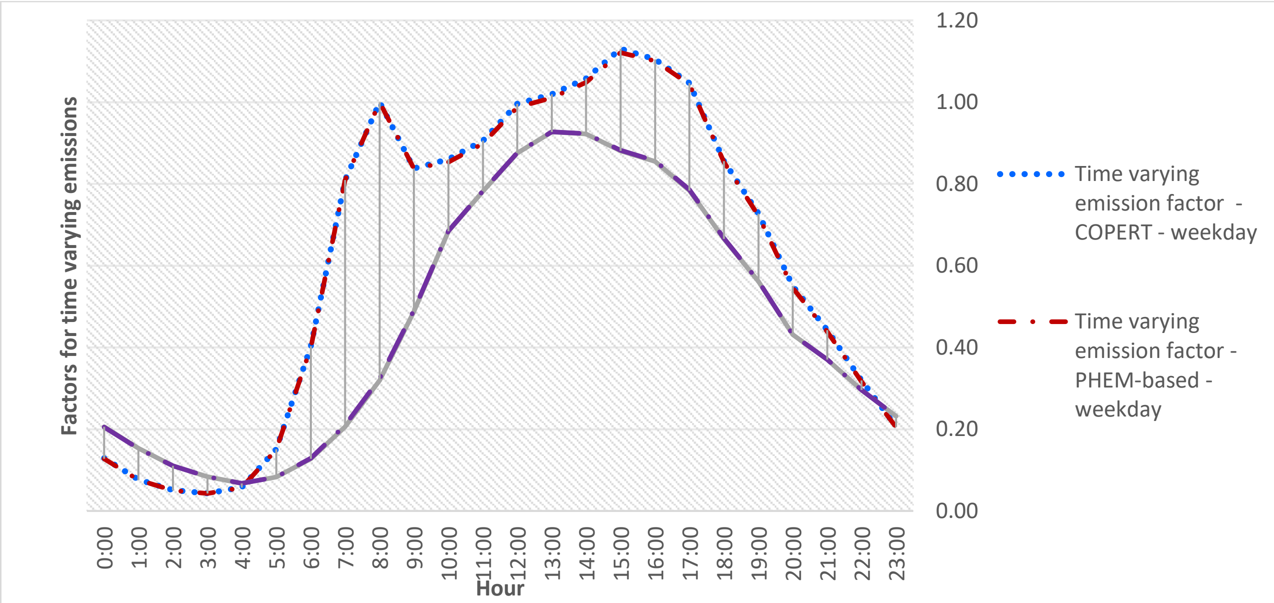


Figure 56 COPERT and PHEM-based Time Varying Emission Factors for Average Weekdays and Weekends used in ADMS-Urban, Source: Own Work (Excel)

E. Output Points (Grids Data)

The grids data screen within the model allows the user to define the points at which the air pollution concentrations, of NO_x in this case, will be output by the model (Cambridge Environmental Research Consultants Ltd, 2010). 46,452 specified output points within Bradford were selected at which the NO_x concentrations will be output by the model. The specified output points covered a box of ≈ 40 * 33 km and were exactly the same points used to construct another LUR air pollution model in Bradford, which estimated NO_x concentrations at a spatial resolution of 100 * 100 m grids (de Hoogh et al., 2014). Each of the 46,452 specified output points represented the middle point of a 100 * 100 m grid. Although TRAP can vary within these 100 * 100 m grids, a finer grid was not considered feasible in this study due to the impracticality of running the ADMS-Urban model multiple separate times to allow for a higher number of output points (the maximum total number of output points possible to enter in one run is 51,005) and as the model run times was very long (see Section 5.3.4.) and partly depended on the number of specified output points (Cambridge Environmental Research Consultants Ltd, 2014). A finer grid was also not expected to have a crucial impact on the final results, due to the nature of this study where air pollution concentrations are finally averaged over census tracts for the health impact assessment (Chapter 6). Finally, the 100 * 100 m grids enabled a meaningful comparison with the results of the widely used LUR TRAP models (Khreis and Nieuwenhuijsen, 2017). Another 126 points representing the locations of 118 diffusion tubes and 8 fixed-site monitoring stations in Bradford were added and their data was used for validation. These points differed in locations, coverage, site selection and purpose (Table 22), and therefore, allowed to explore the impact of different validation datasets on air quality modelling performance (Khreis et al., 2017a).

Table 22 NO_x and NO_2 Measurements Sites in Bradford used for Models' Validation

Measurement campaign and dataset	Pollutants measured	Measurement device	Year and time interval for final dataset	Locations and purpose of measurements	Reference

ESCAPE ***diffusion tubes*** (n=41)	NO_2 and NO_x	Ogawa badges	2009 (annualized)	At the façade of homes of study subjects as the primary objective of the ESCAPE project was to characterize residential exposures and associated health	Cyrys et al. (2012)
CBMDC ***diffusion tubes*** (n=29)	NO_2	"Diffusion tubes"	2009 (annualized)	Three sites were not close to main road whilst the rest were kerbside sites at 0.5-5m from the nearest road, monitoring undertaken to review and assess air quality progress	City of Bradford Metropolitan District Council (2010) (internal document)
De Hoogh ***diffusion tubes*** (n=48)	NO_2	Palmes tubes	Four 2-week periods during 2007-2008	Close to the front door of 48 homes of study subjects from the BiB cohort to characterize their residential exposures	Smith (2011)
CBMDC ***fixed-site monitoring*** (n=8)	NO_2	Automatic urban network (chemiluminescence)	2009 (annualized)	Two sites were classified as urban background whilst the rest were kerbside sites at 1.5-2 m from the nearest road, monitoring undertaken to review and assess air quality progress	City of Bradford Metropolitan District Council (2010) (internal document)

F. Outputs Format Data

NO_x was selected as the output pollutant to be modelled over the "long term". The averaging time selected was 1 hour (which matches the hourly time step used in the meteorological data). The unit for outputs was selected as µg/m^3. The output file (filename.*plt*) contained a single set of NO_x concentration data averaged across all lines of meteorological data for each specified output point.

5.3.4. Set-Up of ADMS-Urban

ADMS-Urban version 3.0.0. was used in this study. A temporary license for the study was loaned by CBMDC. The only additional (advanced) model option which was used in the runs was the time varying emission factors (see above), and this is considered as a theoretical advancement to standard practice (de Hoogh et al., 2014, City of Bradford Metropolitan District Council, 2013). The other additional (advanced) model options were not considered relevant and, therefore, were not selected.

The input data described above was entered in the correct ADMS-Urban format. Excluding multiple trial and verification runs, the model was run 36 times, splitting the 4500 road lines into smaller groups of 500 roads for each run:

- COPERT emission model, 9 runs, each with 500 roads – original locations
- COPERT emission model, 9 runs, each with 500 roads – snapped locations
- PHEM-based emission model, 9 runs, each with 500 roads – original locations
- PHEM-based emission model, 9 runs, each with 500 roads – snapped locations

On average, each run took 5 days (run time only), adding up to over 6 months of model runs only, which the author undertook in parallel on 4 (onsite and remote) computers, to minimize the run times.

5.3.5. NO_x to NO_2 Conversion Data

The proportion of NO_x that is NO_2 in exhaust emissions (termed primary NO_2) is highly uncertain and variable, with wide ranges documented in the literature e.g. between 5% to 60%, across different vehicle classes, fuels, EURO emission standards, and exhaust after-treatment technologies (Carslaw et al., 2011a, Cambridge Environmental Research Consultants Ltd, 2010, Mavroidis and Chaloulakou, 2011, Rhys-Tyler, 2017, Sjödin and Jerksjö, 2008). Further, secondary NO_2, produced in the atmosphere by complex photochemical processes e.g. depending on O_3 concentrations, contributes significantly to final ambient NO_2 concentrations (Mavroidis and Chaloulakou, 2011). Thus, converting NO_x to NO_2, especially at the emission estimation stage, is an uncertain process. In this study, the conversion was undertaken for the final dispersion modelling output of NO_x concentrations. To convert these NO_x concentrations to NO_2 concentrations, an average ambient NO_2/NO_x ratio was used. This was derived from the ESCAPE diffusion tubes administered in Bradford between 1 June 2009 and 15 December 2009. The diffusion tubes measured both NO_2 and NO_x concentrations using Ogawa passive samplers at 41 sites across Bradford (Cyrys et al., 2012). These measurements were used to develop two LUR models in Bradford for NO_2 and NO_x. The measurement sites were classified as regional background (n=2), urban background (n=24) and traffic sites (n=15). The samplers contained two collection filters which were coated with a reactive chemical, one for sampling NO_2 and the other for NO_x (Cyrys et al., 2012).

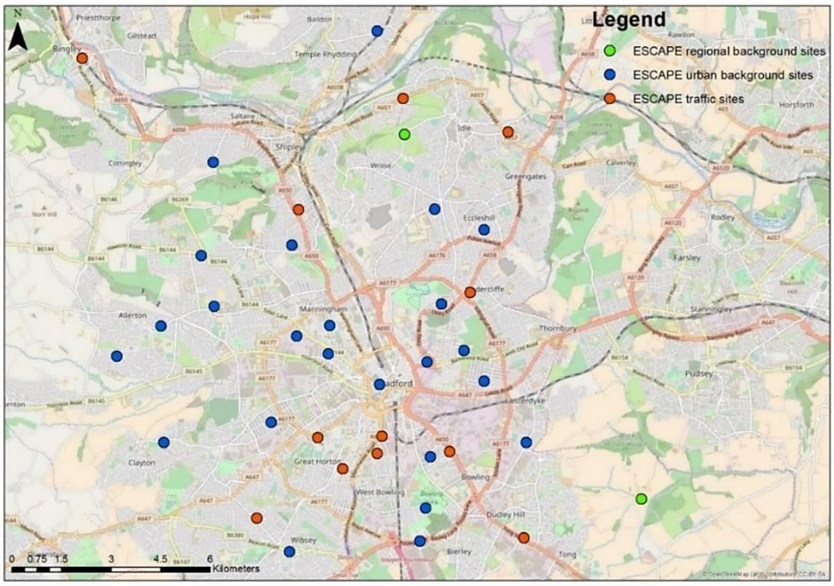


Figure 57 Locations of the ESCAPE's NO_2 and NO_x Ogawa Passive Samplers in Bradford annotated by Site Type, Source: Own Work (Arc Map 10.4)

Measurements were typically made at the façade of homes as the primary objective of the ESCAPE project was to characterize residential exposures and associated health outcomes (Cyrys et al., 2012). Therefore, the air pollution levels measured were generally representative of residential exposures and not e.g. roadside levels. At each site, measurements were made for three 14-day periods, with each period representing a different season namely the warm, cold and intermediate seasons. The measurements were adjusted for temporal variations using measurements obtained from a reference fixed-site monitoring station which was operated all year around (Cyrys et al., 2012, Beelen et al., 2013). The correlation between the adjusted and unadjusted concentrations was high (R^2 > 0.95), indicating that temporal adjustment only had a small effect on the calculated average concentrations (Cyrys et al., 2012). The summary statistics of the adjusted measurements made at these 41 sites are shown in Table 23. The NO_2/NO_x ratio ranged from 0.39 to 0.75 with a calculated average of 0.60; which was used for NO_x to NO_2 conversion in this study. This average ratio was consistent with the average ratio of 0.59 calculated for 36 study areas across Europe and with ratios calculated for English cities like Manchester (0.58) and London/Oxford (0.58) (Cyrys et al., 2012).

Table 23 Summary Statistics of Adjusted Measured NO_2 and NO_x Concentrations at 41 ESCAPE Sites

ESCAPE site type	Rural background	Urban background	Traffic
Definition	Measurements in the smaller towns and villages of the cohort	A site with fewer than 3000 vehicles per day passing within a 50 meters radius	A site in a major road carrying at least 10,000 vehicles per day
Number	2	24	15
Average adjusted NO_2 (µg/m^3)	16.9	24.1	29.7
Average adjusted NO_x (µg/m^3)	23.6	38.4	59.4
Average NO_2/NO_x ratio (µg/m^3)	0.72	0.63	0.50
Minimum adjusted NO_2 (µg/m^3)	16.7	17.2	19.4
Maximum adjusted NO_2 (µg/m^3)	17.0	34.1	44.9
Minimum adjusted NO_x (µg/m^3)	22.4	25.1	33.6
Maximum adjusted NO_x (µg/m^3)	24.7	59.1	110.5

5.3.6. Outputs Validation

The NO_x concentrations output by the dispersion models were validated against measurements from the 126 measurement sites described in Table 22. Differences between the snapped and the original models were explored. Differences between the models with and without minor road and cold start concentrations were also explored. Further, results from the two dispersion models were compared to each other and to the Bradford's ESCAPE LUR model results at the same 46,452 specified output points.

5.4. Results

5.4.1. NO_x Inventories from Traffic and Emissions Linkage

Results from the 24 hours' (average weekday) traffic and average-speed-emission functions linkage are shown in Figure 58 and Table 24. The results broken into the specific modelled vehicle classes are shown in the supplementary data of Khreis et al. (2017b). Figure 58 shows that, when linked with the SATURN outputs, the total NO_x emission inventory estimated with the PHEM-based emission model was 17% lower than COPERT. Further, the two emission models estimated different NO_x emission contributions (in percentage) from the different vehicle classes. The key differences were in the: 1) petrol passenger cars fleet; 2) diesel LDVs; 3) HDVs and 4) buses and coaches. The diesel passenger cars and petrol LDVs source apportionments from the two models were very similar (Figure 58).

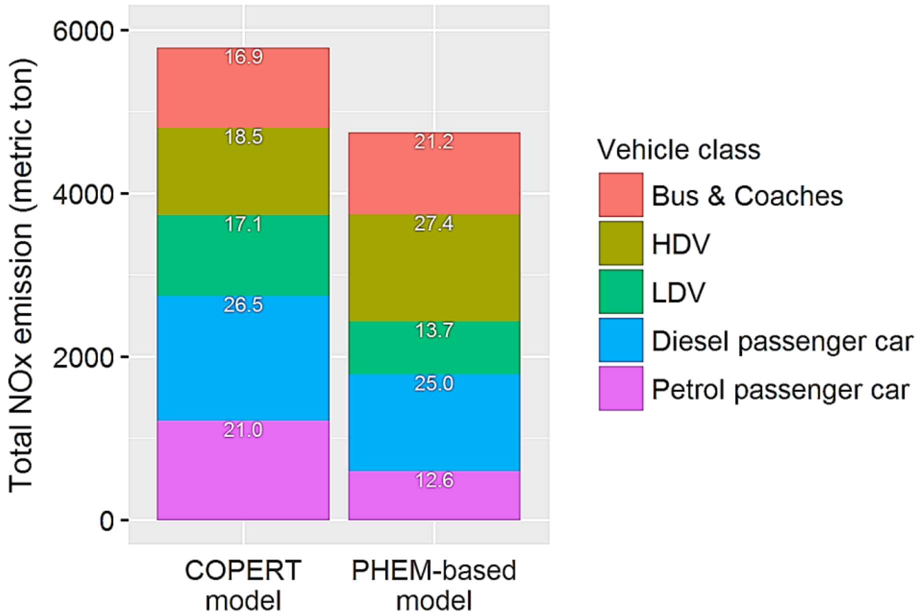


Figure 58 Total NO_x Emissions over the Bradford Road Network on an average weekday as estimated using COPERT and PHEM-based Average-Speed Emission Functions. Vehicle Class Contribution are indicated in white (rounded the nearest tenth of percent), Source: Own Work (R)

The PHEM-based emission model estimated that petrol cars contribute almost 13% of all NO_x compared to 21% estimated from COPERT. Another key difference was in the contribution of HDVs and buses and coaches to total NO_x, where apportionment using the PHEM-based model estimated that these vehicle classes are the most polluting; accounting for 48% of all traffic-related NO_x in Bradford, when combined; as compared to 35% of all traffic-related NO_x as estimated by COPERT. Across the different vehicle classes, the differences between the two models, applied to Bradford's traffic mix and average speeds (Chapter 3) ranged from around -51% to 39% (Table 24). As shown in Table 24, the NO_x COPERT estimates were noticeably higher for passenger cars and for diesel LDVs. On the other hand, the PHEM-based NO_x estimates were higher than the COPERT estimates for petrol LDVs across the three weight categories and for almost all the HDVs, buses and coaches.

Table 24 Vehicle Class Contribution (magnitude in kg and %) to Total NO_x Emissions over the Bradford Road Network on an Average Weekday (24-hour totals) as estimated using: 1) COPERT and 2) PHEM-based Emission Factors

Vehicle class/weight category	NO_x (kg) using COPERT	% of total NO_x	NOx (kg) using PHEM	% of total NO_x	% difference between PHEM and COPERT NO_x
Petrol cars	1212.85	20.97	598.62	12.52	-50.64
Diesel cars	1534.98	26.54	1188.58	24.85	-22.57
Petrol LDVs Class I	2.14	0.04	2.31	0.05	7.91
Petrol LDVs Class II	11.02	0.19	12.36	0.26	12.16
Petrol LDVs Class III	28.82	0.50	34.44	0.72	19.51
Diesel LDVs Class I	40.55	0.70	29.64	0.62	-26.91
Diesel LDVs Class II	250.40	4.33	141.34	2.96	-43.55
Diesel LDVs Class III	654.88	11.32	464.18	9.71	-29.12
HDV Rigid 0-7.5t	129.74	2.24	178.33	3.73	37.44
HDV Rigid 7.5-12t	36.18	0.63	39.43	0.82	9.01
HDV Rigid 12-14t	16.19	0.28	16.57	0.35	2.34
HDV Rigid 14-20t	98.58	1.70	96.54	2.02	-2.07
HDV Rigid 20-26t	165.17	2.86	171.95	3.60	4.10
HDV Rigid 26-28t	85.61	1.48	99.37	2.08	16.08
HDV Rigid 28-32t	193.00	3.34	229.31	4.79	18.82
HDV Rigid ≥ 33t	49.93	0.86	68.98	1.44	38.16
HDV Articulated 0-20t	4.96	0.09	4.66	0.10	-5.99
HDV Articulated 20-28t	8.41	0.15	9.16	0.19	8.92
HDV Articulated 28-34t	6.55	0.11	8.49	0.18	29.71
HDV Articulated 34-40t	53.31	0.92	72.99	1.53	36.91
HDV Articulated 40-50t	221.21	3.83	306.60	6.41	38.60
Buses Single-Decker	170.58	2.95	173.76	3.63	1.86
Buses Double-Decker	478.01	8.27	474.11	9.91	-0.82
Coaches Small	155.09	2.68	156.31	3.27	0.78
Coaches Large	174.55	3.02	204.51	4.28	17.16
ALL VEHICLES	5782.71	100	4782.54	100	-17.30

A closer look at the results broken into the unique 167 vehicle classes within the fleet revealed that the major differences between the two emission models were largely explained by particular classes (supplementary data of Khreis et al. (2017b)). For example, differences between the petrol passenger car inventories were driven by differences in estimates for the EURO 0 vehicles, where COPERT estimates were 81% higher than the PHEM-based one.

COPERT is expected to be less reliable for short road segment lengths and for traffic conditions characterised by high degree of saturation, implying stop-start driving and low average speeds (Chapter 4). The impact of this limited reliability in the comparison of NO_x emissions estimated by the PHEM-based and COPERT emission models was examined through an analysis of the ratio of the estimates from the PHEM-based and COPERT models. Figure 59 shows that, for average speeds between 0 and 10 km/h, this emission ratio is higher than 1 across almost all vehicle classes (from 1.21 to 4.04), meaning that NO_x emissions estimated with the PHEM-based model are higher than those estimated with COPERT. For speeds above 10 km/h, the emission ratio is consistently lower across all vehicle classes and speed values, except for HDV and sometimes buses and coaches. More specifically, the ratio values remain below 1 for passenger cars and LDVs, above 1 for HDVs, and range from 1.09 to 0.81 for buses and coaches. This sudden drop in the ratio, which is inconsistent with the smooth decrease at higher speeds, is likely due to the way COPERT emissions at the lowest speeds are estimated, i.e. applying a constant emission factor for speeds below a threshold of 10 or 12 km/h (Section 4.3.9.).

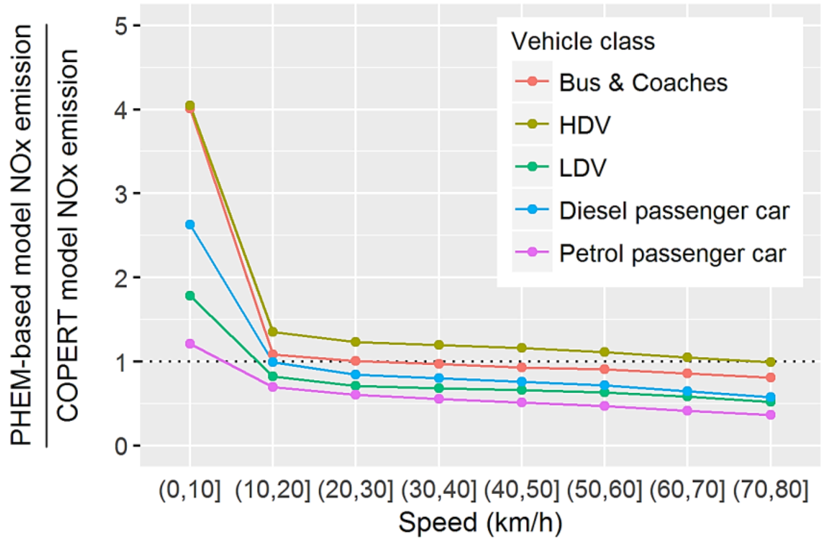
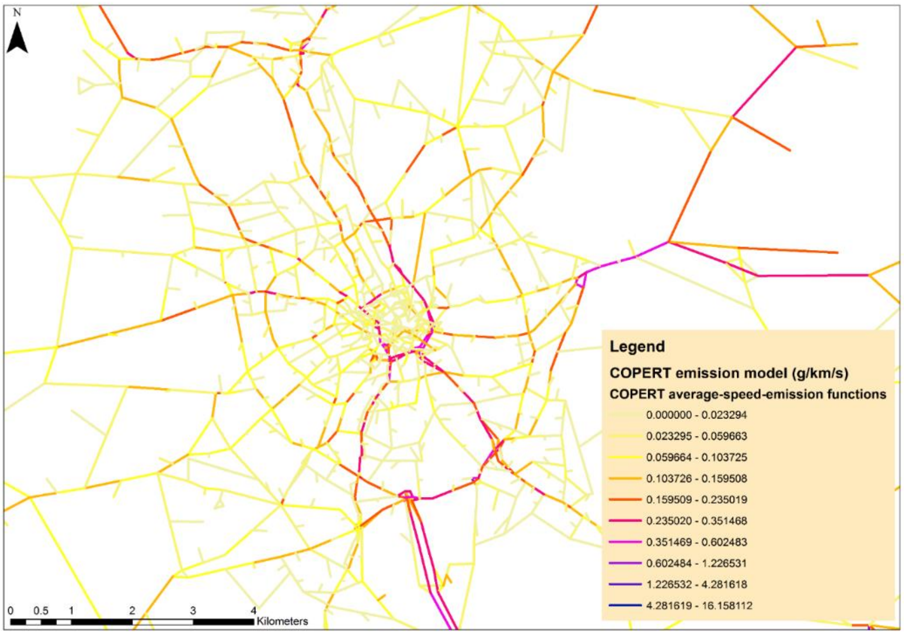


Figure 59 Influence of average speed on difference in NO_x emission of PHEM-based and COPERT models, Source: Own Work (R)

The spatial distribution of the emission rates (g/km/s) as estimated from the two emission models differed slightly (e.g. see Figure 60 which shows the spatial distribution of the emission rates, focused on the Ring Road). The differences were subtle and were mainly that emissions from the roads radiating from the Ring Road were smaller when using the PHEM-based model whilst the emissions within the Ring Road were higher using the PHEM-based emission model, something which has to do with the lower average speeds on inner-city road links.



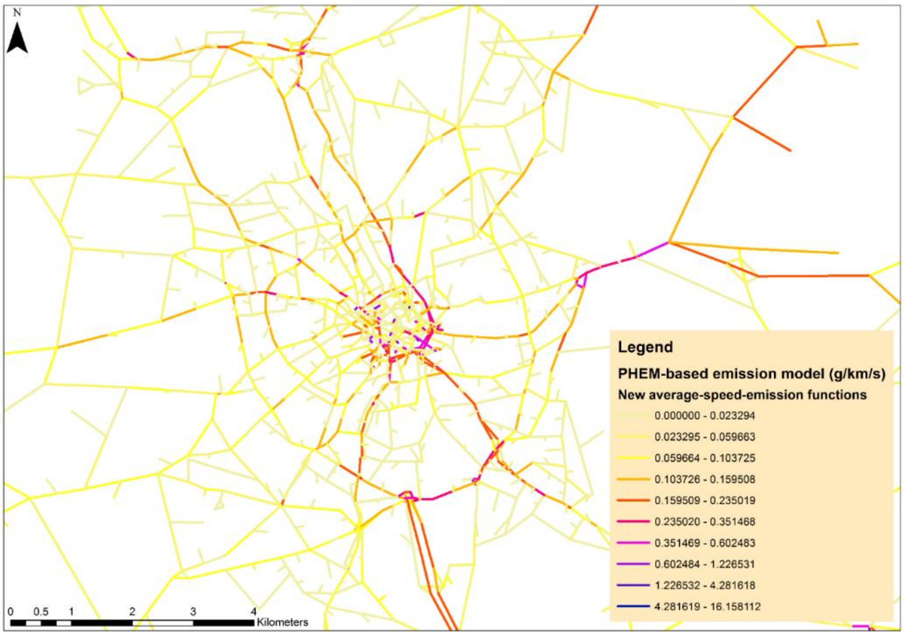


Figure 60 Bradford Spatial Distributions of Traffic-Related NO_x from COPERT (above) and PHEM-based (below) Emission Model, Source: Own Work (Arc Map 10.4)

5.4.2. Meteorological Data

In 2009, prevailing wind in Bradford was from the West, particularly the South West. The average temperature was 9 C^o and the average wind speed and relative humidity were 4 m/s and 86%, respectively.

5.4.3. Dispersion Modelling NO_x Concentrations

The results of the dispersion models' NO_x at the 46,452 specified output points (Section 5.3.3) were considered as the traffic (contribution to the total) NO_x at these locations. These are shown in Table 25. For the COPERT-based dispersion model, these ranged between 0.20 to 93.14 µg/m^3 with a mean of 2.45 µg/m^3. For the PHEM-based dispersion model, the range was wider between 0.18 to 368.45 µg/m^3 with a lower mean of 2.21 µg/m^3. The distributions of these values were skewed to the right as the levels at most of the specified output points were low, as shown in Figure 61.

Table 25 Summary Statistics of Traffic-related NO_x (µg/m^3) Estimated by COPERT and PHEM-based Dispersion Models at the 46,452 Specified Output Points

Statistic	COPERT-based dispersion model	PHEM-based dispersion model
Minimum	0.20	0.18
1st quartile	0.67	0.61
Median	1.33	1.17
Mean	2.45	2.21
3rd quartile	2.58	2.24
Maximum	93.14	368.45

The addition of the varying background NO_x from DEFRA's map to the traffic NO_x at the 46,452 specified output points was considered to account for all other sources of air pollution. The NO_x background map was intersected with the 46,452 output points and the values of the map layer at those points were extracted. There were 21,914 points (47%) where there was no intersection between the output points and the underlying NO_x background map. At those points, the average background NO_x level from the other valid points (equal to 17 µg/m^3) was added to the traffic NO_x, instead. Most of these non-intersecting points fell outside the Bradford's area designated census tracts and were, therefore, not expected to impact the following health impact assessment; conducted at census tract level (Chapter 6).

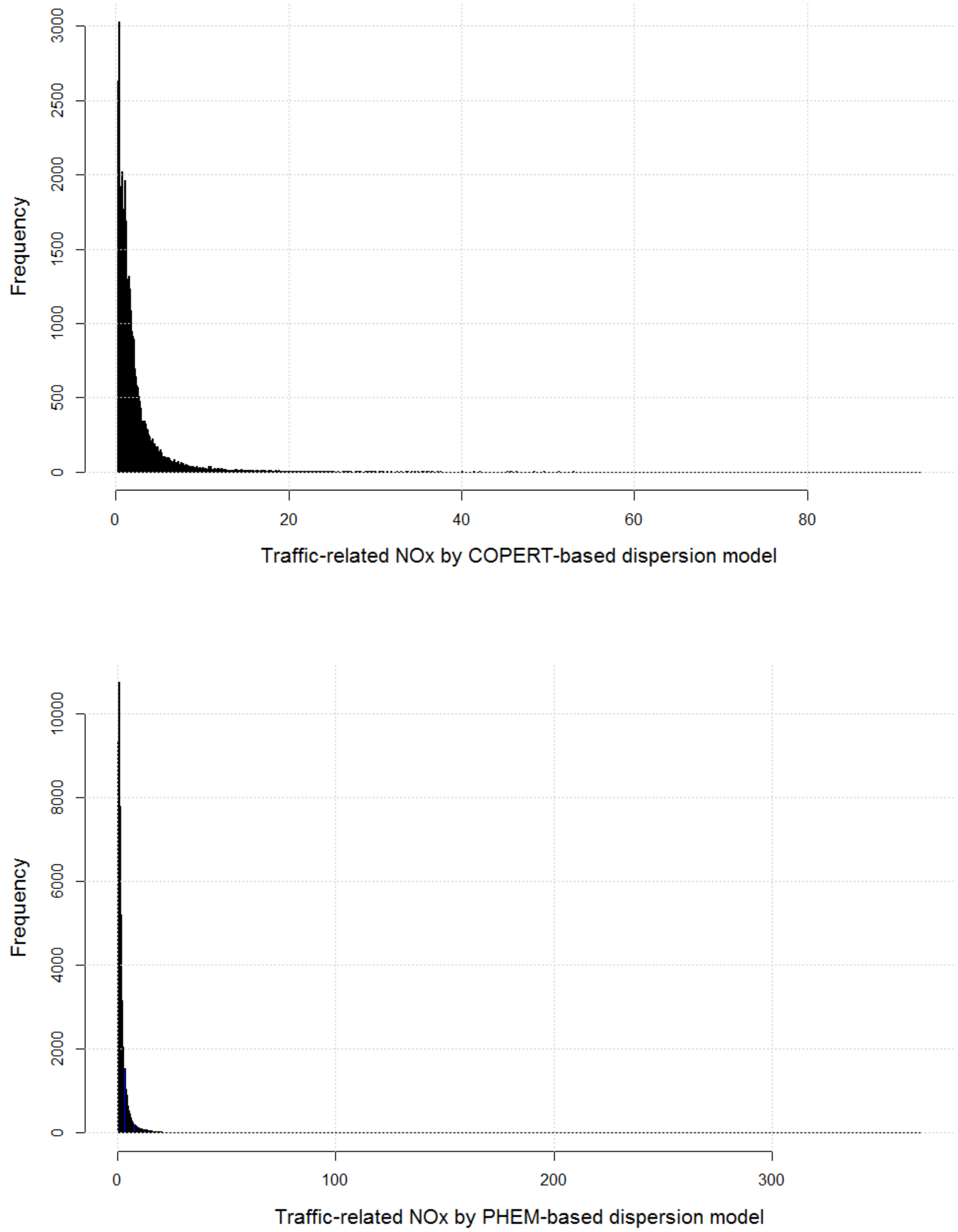


Figure 61 Histogram of Traffic-Related NO_x Estimated by COPERT and PHEM-based Dispersion Models, note the X and Y Axes are different, Source: Own Work (R)

Figure 62 shows the relation between the total NO_x estimates from the COPERT-based and the PHEM-based dispersion models, at the 46,452 specified output points, with background NO_x added. Overall, there was a high correlation between the two models' estimates as reflected in the fitted linear model (with a forced intercept of 0, as the two methods are similar) and it's R^2 value of almost 90%. At 95% of the specified output points, the PHEM-based model estimated less NO_x than the COPERT-based model (ranging from - 0.0006% to - 43.73%, on average by - 1.6%). Conversely, at 2318 (5% of the) specified output points, the PHEM-based model estimated more NO_x than the COPERT-based model's estimates with a difference ranging from + 0.0004% to + 88.10% (on average by + 4.4%).

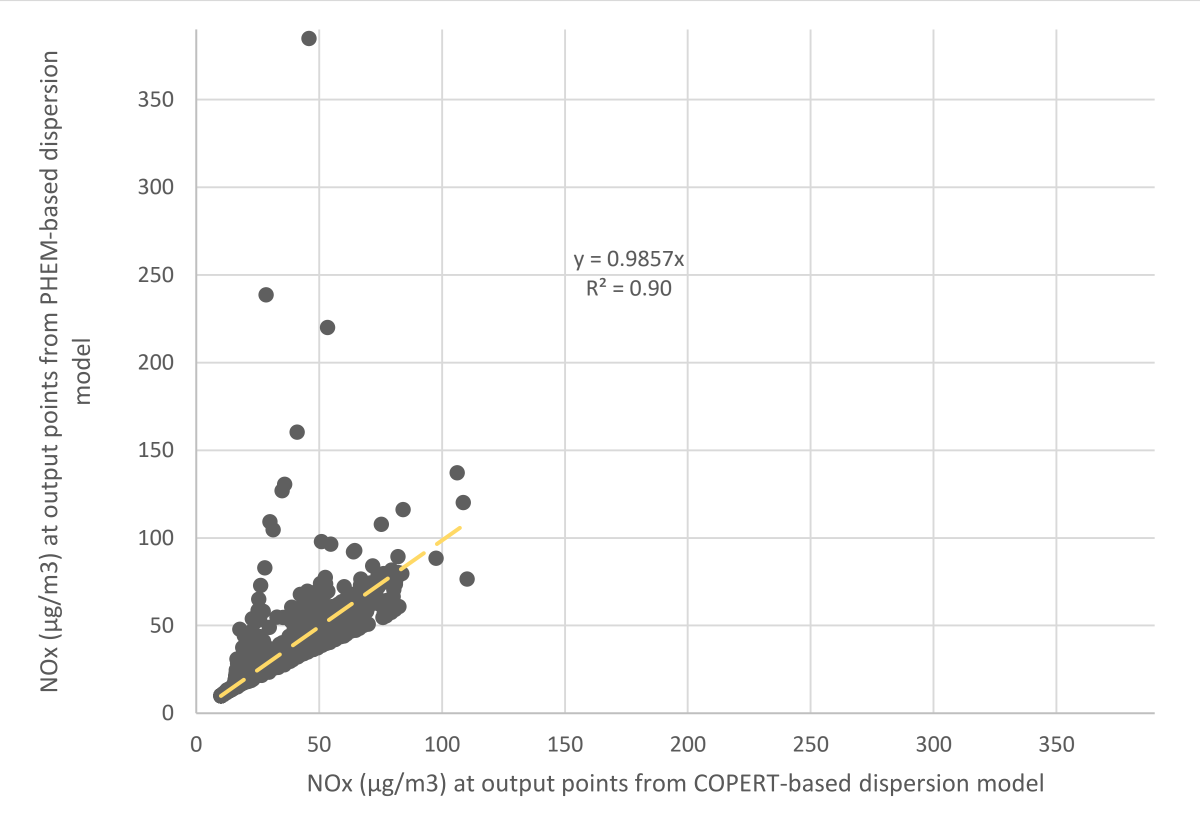


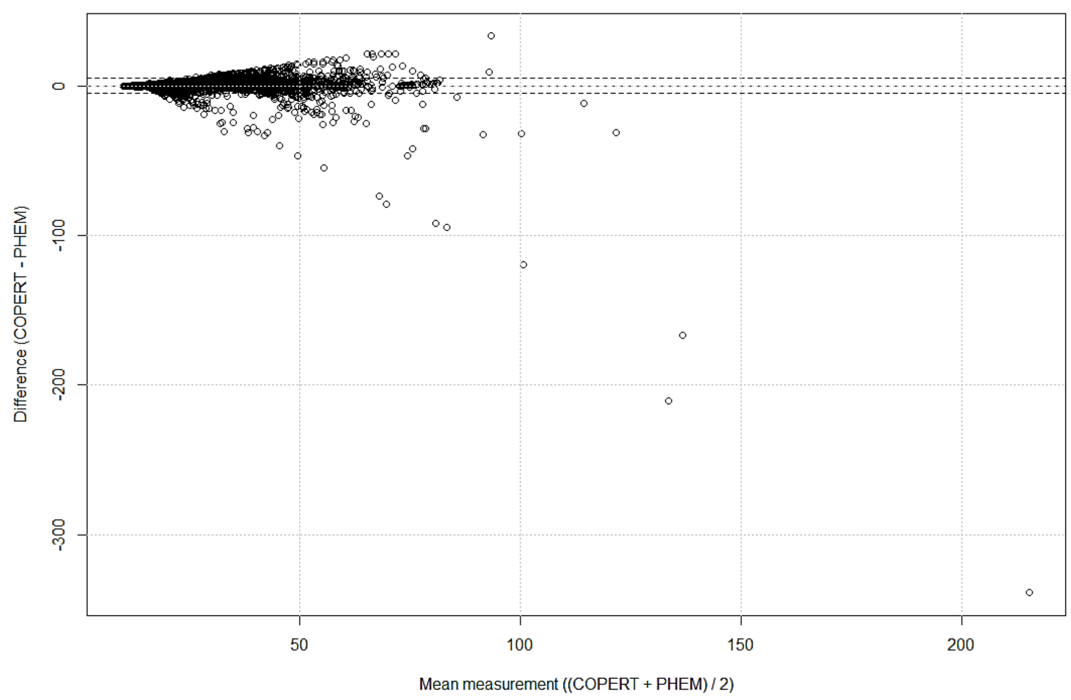
Figure 62 COPERT-based versus PHEM-based Dispersion Modelling NO_x Estimates ($\mu g/m^3$) at the 46,452 Specified Output Points, Source: Own Work (Excel)

Figure 63 shows the Bland-Altman agreement plots (Bland and Altman, 2007) for NO_x estimates/results from the COPERT-based versus the PHEM-based dispersion models. At panels a, b and c, different y-axes scales have been used for easier comparison and visualization. On the y axis is the absolute difference between the COPERT-based and PHEM-based dispersion modelling results whilst on the x axis is their mean. The upper and lower dashed lines represent the 95% CI whilst the middle-dashed line is the mean difference.

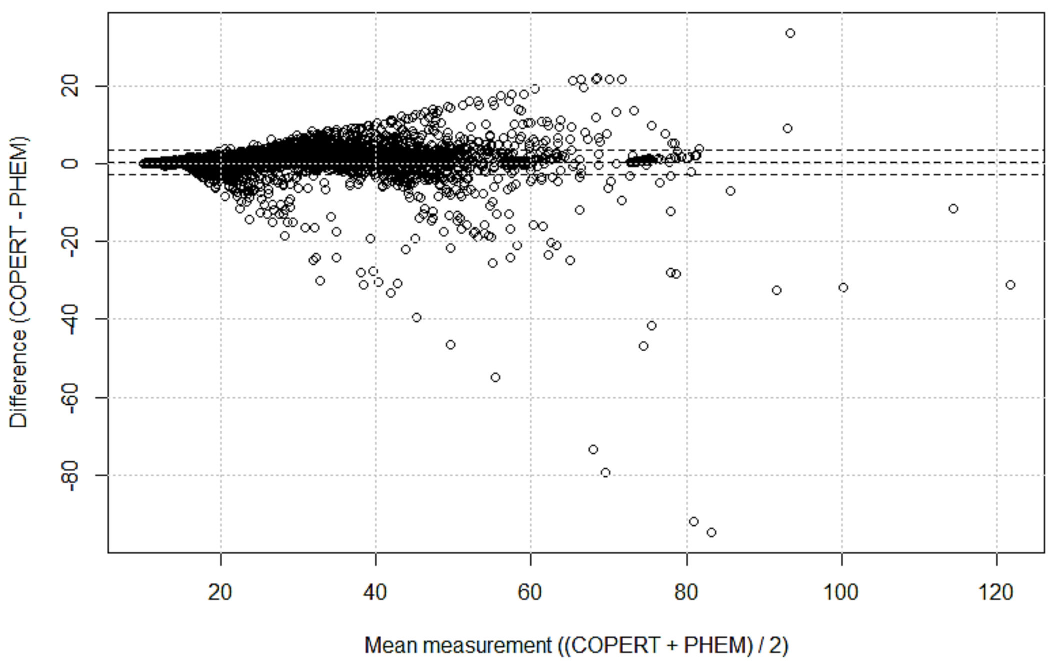
As shown in panel a (top), the large differences in the two models estimates were most apparent with 4 points where the PHEM-based dispersion model estimated NO_x levels higher than the COPERT-based model's estimates by > 100 µg/m^3. The difference between the two models seemed to increase with the increasing means (moving to the right). This is likely to be due to the high and increasing PHEM-based estimates which bring both the mean (x axis) and the difference between the two models (y axis), up. A further look at these points showed that they were far at the edges of the simulated network and were adjacent to road links with 0.33 (link ID 3065_3052) and 0.1 km/h (link ID 1257_1255) traffic speeds and 1275 and 1946 PCU/h AM, one-way, traffic flows, respectively. Two of the four points were also in proximity of a major roundabout (the Chain Bar roundabout/interchange). No other specific explanation for the differences here was ascertained.

Zooming in, panel b (middle) shows a similar trend: the PHEM-based dispersion model estimates higher NO_x at a few points only and the difference seems to increase with the increasing mean, likely due to the high and increasing PHEM-based estimates. However, on the top part of the graph, it is clear that the COPERT-based model estimates higher NO_x at a much larger number of receptor points, but that the differences in the two models estimates at these points are not as stark (i.e. the top part of the funnel is not so wide as the lower part).

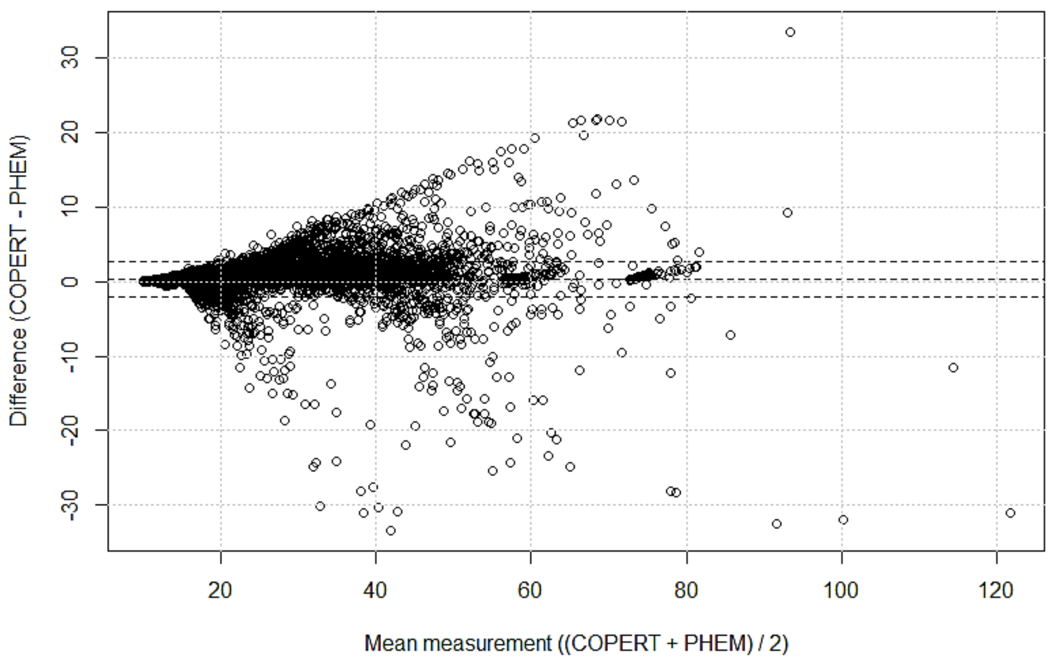
Finally, zooming in further as shown in panel c, confirms the above point showing that the COPERT-based model estimates higher NO_x at most of the receptor points and that the difference between the two models' estimates is not as stark in this case (maximum difference between the COPERT-based and the PHEM-based models' estimates is just above 30 µg/m^3). These trends are likely to be due to the combination of differences in the emission functions (Chapter 4) and speeds data available from the SATURN model (Chapter 3). The PHEM-based emission functions estimate very high NO_x at the lower speeds (lower than 10 km/h) with stark differences to the COPERT functions (Figure 51 and Figure 59); yet only a small proportion of the SATURN links (< 12%) have speeds less than 10 km/h and as such the density of these points, with such stark differences, is low. On the other hand, the COPERT-based functions estimate higher NO_x at the middle and higher speeds (> 10 to 80 km/h); speeds which most of the SATURN road links have, yet at these points the differences between the two methods is not so stark (Figure 51 and Figure 59). The importance and relevance of these observations is further discussed in Section 5.5.2.



a) All 46,452 specified output points



b) 4 data points, where COPERT-PHEM < -100 (-167, -339, -210, -119), removed from (a) to enable better visualization



c) 13 data points, where COPERT-PHEM < -35 (maximum difference between COPERT and PHEM = 35), removed from (b) to enable better visualization

Figure 63 Bland−Altman Agreement Plots for COPERT-based versus PHEM-based Dispersion Modelling, Upper and lower dashed lines: 95% CI, Middle dashed line: mean difference, Source: Own Work (R)

5.4.4. Dispersion Modelling Comparison to LUR

Figure 64 shows the relation between NO_x estimates from the COPERT-based dispersion model and the LUR model. Figure 65 shows the relation between NO_x estimates from the PHEM-based dispersion model and the LUR model, both at the 46,452 specified output points. As shown in Figure 64, a linear model between NO_x estimates from the two methods only captured 25% of the variability (r = 0.50), indicating that there is not a good correlation between the estimates from the two models. At 37,548 (81% of the) specified output points, the COPERT-based model estimated NO_x levels that are lower than the LUR model (ranging from - 0.0007% to - 296.33%, on average by - 57.5%). At the remaining 8,904 specified output points, the COPERT-based model estimated NO_x levels that are higher than the LUR's by + 0.0109% to + 100% (on average by + 76.86%).

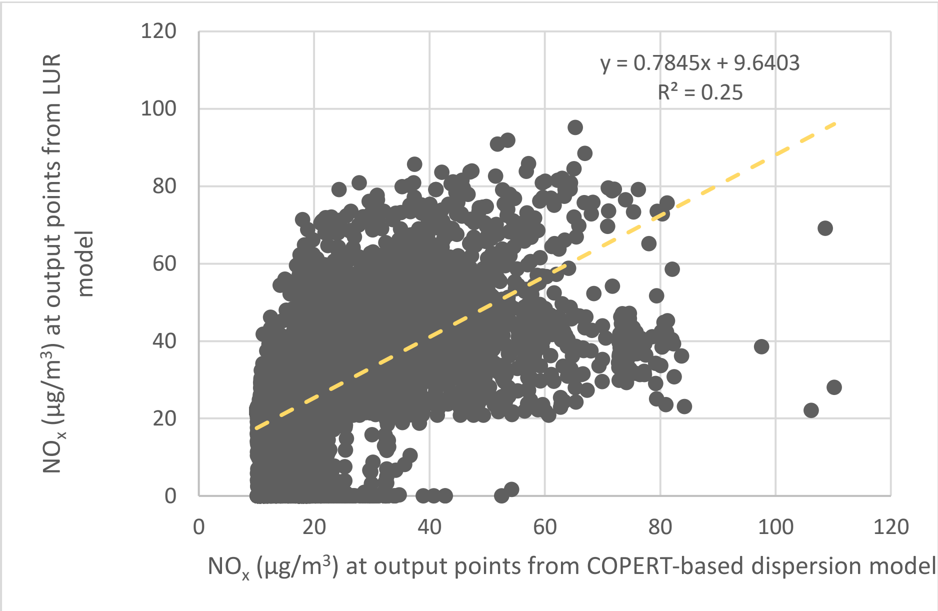


Figure 64 COPERT-based Dispersion Modelling versus LUR Model NO_x Estimates ($\mu g/m^3$) at the 46,452 Specified Output Points, Source: Own Work (Excel)

As shown on the bottom left side of Figure 64, the COPERT-based dispersion model estimated NO_x between about 10 and 50 $\mu g/m^3$ when the LUR estimated almost 0 $\mu g/m^3$ NO_x. This had to do with the fact that LUR equations resulted in negative values at some specified output points e.g. in rural areas (places out of the range in terms of predictor variables where traffic is very low and green space is high). These negative values were set to the minimum NO_x estimated by the LUR; equal to 0.0006 $\mu g/m^3$. The removal of these points (6101 with negative NO_x) improved the correlation, bringing R^2 up by almost 10% to 34% (r = 0.60).

Similarly, Figure 65 shows that a linear model between NO_x estimates from the PHEM-based dispersion model and the LUR model only captured 22% of the variability (r = 0.47), indicating that there is not a good correlation between the estimates from the two models. At 37,796 (81% of the) specified output points, the PHEM-based model estimated NO_x levels that are lower than the LUR model's estimates (ranging from - 0.035% to - 299.64%, on average by - 59.1%). At the remaining 8,656 specified output points, the PHEM-based model estimated NO_x levels that are higher than the LUR's by + 0.0057% to + 100% (on average by + 78.59%). The PHEM-based dispersion model also estimated NO_x values between about 10 and 50 µg/m^3 when the LUR estimated almost 0 µg/m^3 NO_x and this had to do with replacing all the LUR negative values with the minimum NO_x estimated by the LUR (see above). The removal of these points improved the correlation between the two methods, bringing the R^2 up by almost 10% to 31%.

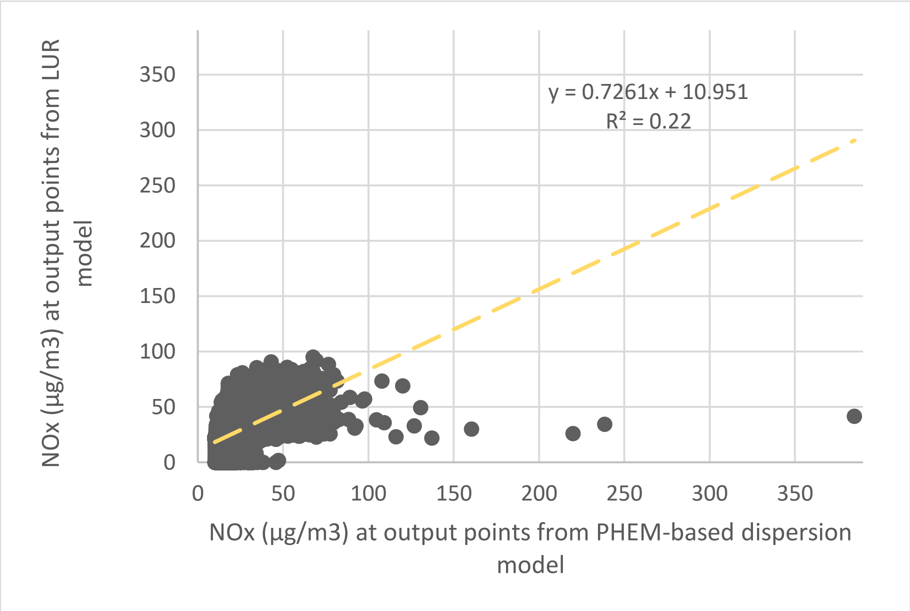


Figure 65 PHEM-based Dispersion Modelling versus LUR Model NO_x Estimates (µg/m^3) at the 46,452 Specified Output Points, Source: Own Work (Excel)

Table 26 shows the summary statistics of the NO_x estimates at the 46,452 specified outputs points from the two dispersion models and the LUR model, alongside the traffic levels in brackets to give an indication of the traffic contribution to the total NO_x; as estimated from the two dispersion models. The range for the PHEM-based dispersion model estimates was wider than that of the COPERT-based model, as reflected by the minimum and specially the maximum values. The PHEM-based model, however, resulted in slightly less NO_x, on average, in line with Figure 62 and Figure 63. In both dispersion models, the contribution of traffic to the total NO_x was modest equalling 2.45 (COPERT-based) and 2.21 (PHEM-based) μg/m^3, on average, and ranging from 0.36 to 313.86 μg/m^3. On the other hand, the LUR estimates had a narrower range and the average NO_x value estimated by the LUR was almost 30% higher than the corresponding values from both dispersion models (Table 26).

Table 26 Summary Statistics of COPERT-based and PHEM-based Dispersion Modelling NO_x Estimates and LUR Modelling NO_x Estimates at the 46,452 Specified Output Points (μg/m^3)

Model and statistic	COPERT-based dispersion model (traffic)	PHEM-based dispersion model (traffic)	LUR model
Minimum	10.03 (0.40)	9.99 (0.36)	0.00064
1st quartile	15.93	15.79	22.00
Median	17.80 (0.78)	17.72 (0.70)	24.93
Mean	**19.47 (2.45)**	**19.23 (2.21)**	**24.91**
3rd quartile	20.34	19.95	32.10
Maximum	110.15 (93.14)	384.94 (368.45)	95.18

Table 27 shows the summary statistics of the NO_2 estimates at the 46,452 specified outputs points from the two dispersion models and the LUR model. For the two dispersion models, NO_2 was generated by conversion (see Section 5.3.5). The range for the PHEM-based dispersion model estimates was wider than the COPERT-based model. The LUR estimates had a narrower range and on average, NO_2 estimated by the LUR was 55% higher than both dispersion models. In both dispersion models, the contribution of traffic to total NO_2 was modest equalling 1.47 (COPERT-based) and 1.33 (PHEM-based) μg/m^3, on average, and ranging from 0.22 to 221.07 μg/m^3.

Table 27 Summary Statistics of COPERT-based and PHEM-based Dispersion Modelling NO_2 Estimates and LUR Modelling NO_2 Estimates at the 46,452 Specified Output Points (μg/m^3)

Model and statistic	COPERT-based dispersion model (traffic)	PHEM-based dispersion model (traffic)	LUR model
Minimum	6.02 (0.24)	5.99 (0.22)	11.36
1st quartile	9.56	9.47	16.91
Median	10.68 (0.47)	10.63 (0.42)	17.87
Mean	**11.68 (1.47)**	**11.54 (1.33)**	**18.12**
3rd quartile	12.20	11.97	20.13
Maximum	66.09 (55.88)	230.96 (221.07)	44.13

Finally, Figure 66 shows the NO_x spatial distribution from the COPERT and PHEM-based dispersion models and from the LUR model. Note that the legend and scale have been unified across the three maps to enable direct visual comparison.

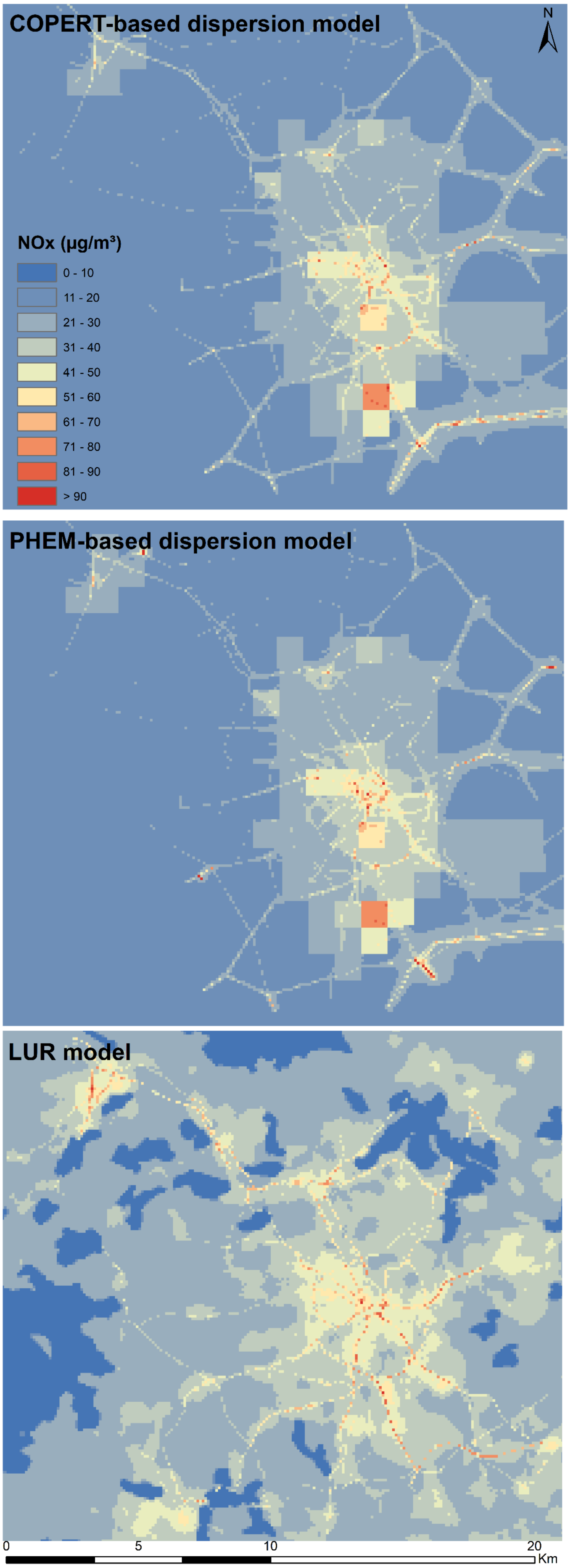


Figure 66 Spatial Distribution of NO_x (µg/m³) across Bradford across the Three Exposure Models, Source: Own Work (ArcMap 10.4)

5.4.5. Models Validation

Table 28 shows results of the different models' validation against the 4 available validation datasets previously described in Table 22. Estimates from the COPERT-based, PHEM-based dispersion models and the LUR model were validated. Each model was used to estimate annual NO_x (directly) or annual NO_2 (by conversion in the case of the dispersion models, see Section 5.3.5.), at the exact locations of the validation points and these estimates were compared to measurements. The dispersion models were complemented with constant or varying background NO_x (see Background Air Quality Data in Section 5.3.3.), to test the impacts of background data on the validation and select the better performing method (Khreis et al., 2017a).

A. Performance of the LUR Models

Table 28 shows that the LUR models have a good performance against the data measured at the 41 ESCAPE sites (which were the measurements used to develop the model), with an R^2 of 0.58 and 0.54 for NO_x and NO_2, respectively. The model performs similarly well at the 48 NO_2 diffusion tubes from the 'De Hoogh' data set (R^2 = 0.61) but this validation is considered less comparable as this dataset comes from a different period (2007/2008). When the LUR model estimates are compared with the CBMDC measurements, the model performs worse with an R^2 of 0.21 and 0.38 in comparison with NO_2 diffusion tubes and fixed-site monitoring data, respectively. Overall, the model under estimated NO_x and NO_2 levels (data not shown).

B. Performance of the Dispersion Models

In comparison to the LUR models, both the COPERT and PHEM-based dispersion models performed worse, and there were no major differences in their performance, indicating that the emission factors were not influential in the models' validity. Using varying background levels, the R^2 of the COPERT-based model at the 41 ESCAPE sites was 0.23 and 0.30 for NO_x and NO_2, respectively. The use of constant background levels resulted in worse performance. At the CBMDC diffusion tubes and continuous fixed-site measurements sites and using varying background levels, the COPERT-based model had an R^2 of 0.23 and 0.28, respectively, compared to 0.24 and 0.16 for the PHEM-based model. The models performed better at the 48 NO_2 diffusion tubes from the 'De Hoogh' data set (R^2 = 0.50 and 0.39). Overall, the dispersion models with the varying background NO_x performed better than those with the constant background NO_x. Because of this and the fact that it is unrealistic to assume that background levels are constant across the whole city, the varying background models were adopted in final analyses (Chapter 6). Overall, both models underestimated NO_x and NO_2 levels (data not shown). For ease of comparison, the R^2 of the models with varying backgrounds are highlighted in light green in Table 28.

Table 28 COPERT and PHEM-based Dispersion Models and LUR Model Validation (rows) against Different Datasets (columns)

Models combination		Validation dataset				
		ESCAPE **NO_x** diffusion tubes (**n=41**)	ESCAPE **NO_2** diffusion tubes (**n=41**)	CBMDC **NO_2** diffusion tubes (**n=29**)	De Hoogh **NO_2** diffusion tubes (**n=48**)	CBMDC **NO_2** fixed-site monitoring (**n=8**)
LUR models	**NO_x** LUR estimates *at points*	R^2= 0.58				
	NO_2 LUR estimates *at points*		R^2= 0.54	R^2= 0.21	R^2= 0.61	R^2= 0.38
COPERT-based dispersion model	COPERT dispersion model **NO_x** *at points* (constant background)	R^2= 0.13				
	COPERT dispersion model **NO_x** *at points* (varying background)	R^2= 0.23				
	COPERT dispersion model **NO_2** *at points* (constant background)		R^2= 0.17	R^2= 0.27	R^2= 0.34	R^2= 0.56
	COPERT dispersion model **NO_2** *at points* (varying background)		R^2= 0.30	R^2= 0.23	R^2= 0.50	R^2= 0.28
PHEM-based dispersion model	PHEM dispersion model **NO_x** *at points* (constant background)	R^2= 0.13				
	PHEM dispersion model **NO_x** *at points* (varying background)	R^2= 0.22				

	PHEM dispersion model **NO_2** *at points* (constant background)		R^2 = 0.17	R^2 = 0.28	R^2 = 0.24	R^2 = 0.32
	PHEM dispersion model **NO_2** *at points* (varying background)		R^2 = 0.29	R^2 = 0.24	R^2 = 0.39	R^2 = 0.16

C. Performance of the Dispersion Models without Influential Points

To further investigate the impact of the COPERT-based versus the PHEM-based emission factors on the validity of the full-chain exposure model developed in this study, additional analysis, focused on the 41 ESCAPE validation data points, was performed. The 41 ESCAPE validation data points were selected for the further analysis as these were the only direct source of NO_x levels, making a direct comparison with the dispersion models' NO_x estimates possible (Khreis et al., 2017a).

Figure 67 shows the relation between the COPERT-based and the PHEM-based dispersion models' NO_x estimates at the 41 ESCAPE site locations (only the traffic-related component, no background levels added). The two models' estimates correlated well and on average, the PHEM-based model tended to estimate lower NO_x than the COPERT-based model, in line with findings of Section 5.4.3.

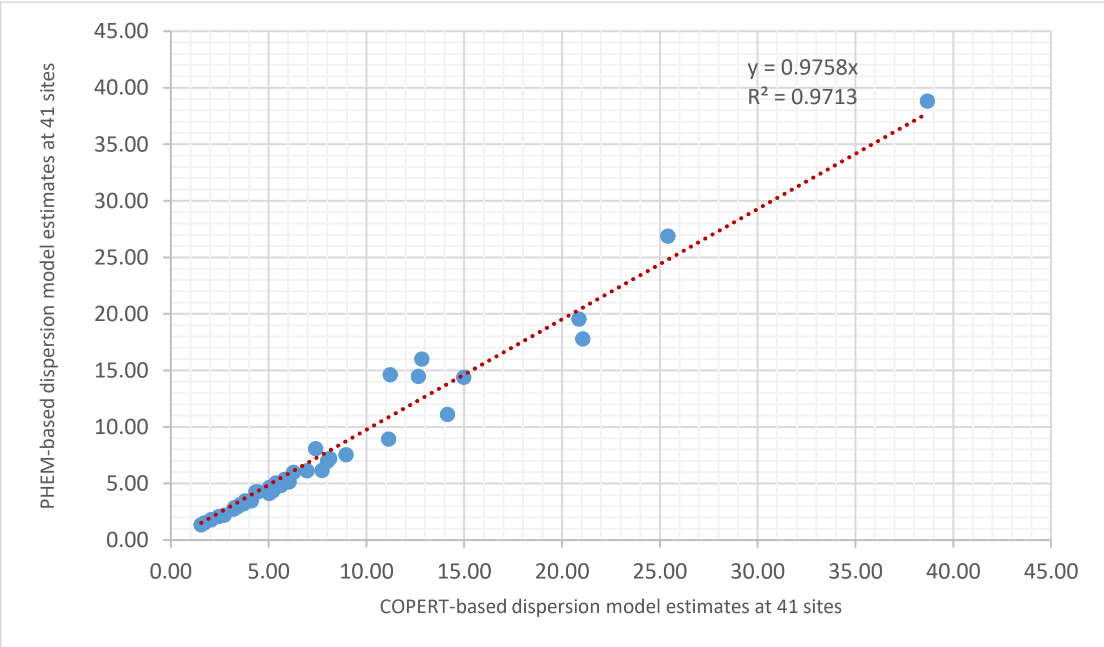


Figure 67 COPERT-based and the PHEM-based dispersion models' NOx estimates at the 41 ESCAPE site locations, Source: Own Work (Excel)

The Bland-Altman agreement plots for estimates from the COPERT-based and the PHEM-based dispersion models (varying background levels added) versus the NO_x measurements at the 41 ESCAPE sites showed no detectable difference in the performance of the two emission estimation methods (Figure 68). There was evidence that the measured NO_x at the 41 ESCAPE sites was generally higher than both the COPERT-based and the PHEM-based dispersion modelling results, as the clear majority of the points in Figure 68 fell above the 0 line (where the ESCAPE measurement – the dispersion model's estimate > 0).

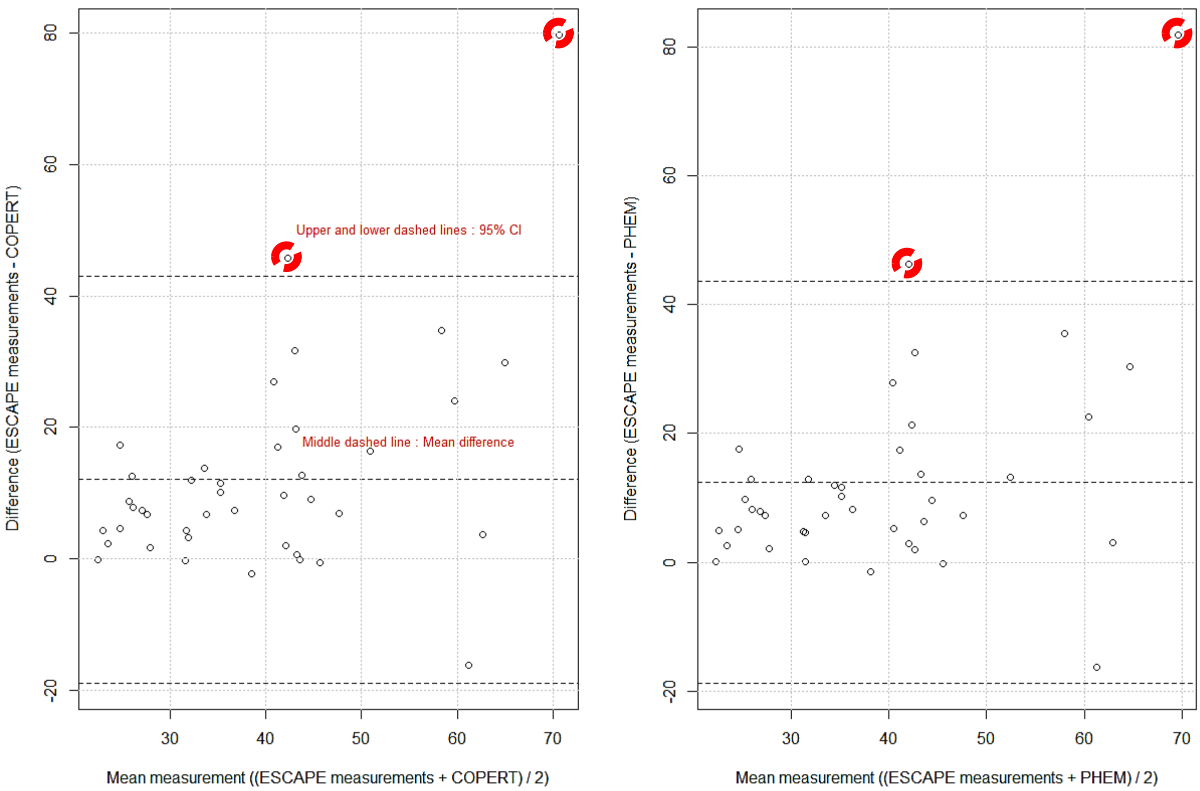


Figure 68 Bland−Altman Agreement Plots for ESCAPE Measurements versus COPERT-based (left) and PHEM-based (right) Dispersion Modelling NO_x estimates, Source: Own Work (R)

Looking at the individual sites, the dispersion models (with varying background added) under estimated NO_x at 35 out of the 41 validation sites by 1.5% to 74.1%; or on average by 15 µg/m^3 NO_x (32%). 14 of these sites were traffic, 20 were urban background sites and one was a regional background site (Table 29). The range and percentage of under estimation from the COPERT-based model, by validation site, are shown in Table 29. These results suggested that TRAP was under estimated at these sites, e.g. due to low emission factors (and overestimated traffic speeds) and the exclusion of some roads and/or that background NO_x levels were not sufficiently captured/were under estimated.

Table 29 ESCAPE Sites Where NO_x was Under Estimated from the COPERT-based model (N = 35/41)

ESCAPE site type	Number	Range of under estimation in μg/m³	Mean of under estimation in μg/m³ (percentage)
Traffic	14	0.65 – 79.66	23.16 (34%)
Urban background	20	1.68 – 26.93	9.36 (24%)
Regional background	1	NA	2.35 (10%)

There were two traffic ESCAPE sites (circled in red in Figure 68) where the difference between the measurements and the dispersion models' estimates were highest and where there was reason to consider these points as outliers (Khreis et al., 2017a, Beelen et al., 2013). These two points were highly influential on the models' validation statistics as their removal increased R^2 from 0.23 (Table 28) to 0.49 for the COPERT-based dispersion model (Table 30) and from 0.22 (Table 28) to 0.50 for the PHEM-based dispersion model (Table 30). Similarly, the removal of these two points increased the LUR's R^2 from 0.58 to 0.73 (NO_x validation).

Table 30 COPERT and PHEM-based Dispersion Models Validation against the ESCAPE NO_x Dataset, without 2 influential sites

Dispersion model combination	ESCAPE **NO_x** diffusion tubes (n=39)	
COPERT dispersion model **NO_x** *at points* (varying background)	r= 0.70	R^2= 0.49
PHEM dispersion model **NO_x** *at points* (varying background)	r= 0.71	R^2= 0.50

5.4.6. Snapped Dispersion Modelling Validation

A. Snapped Dispersion Modelling Validation without Minor Road and Cold Start Concentrations

A concern was that the performance of the dispersion models was related to the inaccurate links geo-locations in the original SATURN network and the fact that road links were represented as straight lines (see Section 3.4.4 and additional analyses in Khreis et al. (2017a)). The snapped SATURN network attempted to increase the accuracy of the links geo-locations (despite not dealing with the issue that the links are represented as straight lines) and was therefore run again in ADMS-Urban. The validation of the snapped models indicated an improvement in the models' performance by up to 12% as shown in Table 31 (comparable to Table 30) and in Table in Annex 5.2. (comparable to Table 28). Therefore, the snapped models were the ones adopted in following health impact assessment analyses (Chapter 6).

Table 31 Snapped COPERT and PHEM-based Dispersion Models Validation against the ESCAPE NO_x Dataset, without 2 influential sites

Dispersion model combination	ESCAPE **NO_x** diffusion tubes (n=39)	
Snapped COPERT dispersion model **NO_x** *at points* (varying background)	r= 0.78	R^2= 0.60
Snapped PHEM dispersion model **NO_x** *at points* (varying background)	r= 0.79	R^2= 0.62

B. Snapped Dispersion Modelling Validation with Minor Road and Cold Start Concentrations

The exclusion of minor roads (and cold starts) from the adopted SATURN traffic network was believed to be one reason behind the under estimation of NO_x documented above and this was investigated further in this analysis.

Adding minor roads and cold start concentrations to the snapped COPERT-based model estimates did not improve the validation metric (R^2) and left it almost unchanged as compared to the main analysis (data not shown). However, the under estimation at the ESCAPE validation sites, as recorded in Table 29, was notably lessened (Table 32), suggesting that the addition of minor roads and colds starts to the SATURN network may improve the model's performance, whilst their exclusion may be one important reason behind the model's under estimation.

Table 32 shows that when minor road and cold start concentrations were added to the snapped COPERT-based model estimates, only 21, instead of 35 sites (Table 29), had a NO_x under estimation. Of those, 10 sites (instead of 14 sites as in the main analysis) were traffic sites where NO_x was underestimated by about 31%, on average, and 11 sites (instead of 20 sites as in the main analysis) were urban background sites, where NO_x was underestimated by almost 12%, on average. Across all the ESCAPE sites combined, NO_x estimates from the ADMS-Urban model with minor road and cold start concentrations were underestimated by 4.9% or 4.7 µg/m^3, on average, as compared to 32% or 15 µg/m^3, on average, in the main analysis (the unsnapped COPERT-based model, without minor road and cold start concentrations).

Table 32 ESCAPE Sites Where NO_x was Under Estimated from the Snapped COPERT-based model *when complemented by minor road and cold start concentrations* (sensitivity analysis) (N = 21/41)

ESCAPE site type	Number	Range of under estimation in µg/m^3	Mean of under estimation in µg/m^3 (percentage)	Median of under estimation in µg/m^3 (percentage)
Traffic	***10***	2.9 – 72.3	22.7 (31.3%)	16.9 (27.8%)
Urban background	***11***	0.6 – 17.5	4.9 (11.8%)	2.7 (7.9%)

5.5. Discussion

5.5.1. Summary

In this work, a full-chain exposure assessment model linking traffic, emissions and atmospheric dispersion models was developed utilizing two different sets of vehicle emission factors (COPERT and PHEM-based). The dispersion models were set-up and run estimating traffic-related NO_x at 46,452 receptor output points in Bradford. These output points covered an area of approximately 40 * 33 km and were identical to those used to establish a LUR model in Bradford (Beelen et al., 2013). The traffic-related NO_x estimates at the output points were added to the background NO_x levels as estimated from DEFRA's background maps (Department for Environment Food and Rural Affairs, 2016a), once excluding minor road and cold start concentrations and once including them. NO_2 was generated by conversion. The dispersion models' estimates were validated, compared to each other and to results from the NO_x and NO_2 LUR models in Bradford. The dispersion models were set-up again with the snapped road network, to attempt to improve the models' performance.

The key results of this work can be summarized as follows. Overall, the total NO_x emission inventory estimated with the PHEM-based emission model was 17% lower than the COPERT's estimate; a finding that was unexpected and is considered to further under estimate already low vehicle emissions and TRAP. The two emission models also resulted in notably different source apportionment; shifting the focus from passenger cars to HDVs (Figure 58) when using the PHEM-based model. In line with findings in Chapter 4, the results showed that the PHEM-based model estimated higher NO_x at speeds below 10 km/h (Figure 59). Results from the dispersion models estimated the traffic-related NO_x which ranged from 0.20 to 93 (mean = 2.45) µg/m^3 for the COPERT-based model and from 0.18 to 368 (mean = 2.21) µg/m^3 for the PHEM-based model. This traffic contribution, on average, was considered low and likely to be under estimated. Indeed, comparison with measurements suggested that these levels, and/or the background levels, were under estimated (Figure 68). The underestimation was lowered, however, when minor road and cold start concentrations from the DEFRA NO_x background maps were added to the estimates (Table 32). Results from the COPERT-based and PHEM-based dispersion models correlated well with each other (R^2 = 0.90; Figure 62). On the other hand, the correlations between the two dispersion models and the LUR model were moderate (Figure 64 and Figure 65). The range of NO_x from the dispersion models was wider than that from the LUR, whilst average NO_x and NO_2 from the LUR was 30% and 55% higher than estimated by the two dispersion models (Table 26). Validation of the models showed that overall the LUR models performed better than the dispersion models, but that the performance was contingent on the validation dataset used; see Table 28 and Khreis et al. (2017a). All models under estimated measured pollution levels. The snapping of the SATURN road network improved the models' R^2.

Obtaining, generating and verifying the required input and validation data, converting it to ADMS-Urban compatible format and setting up and running the ADMS-Urban models proved difficult and highly time consuming and four onsite and remote computers were used to complete the model runs. In terms of practice implications, the main conclusion of this study was that it is no surprise that comprehensive full-chain exposure assessment models are lacking in the literature. Both researchers and local authorities trying to undertake such modelling can benefit from readily available and verified quality input data. Programs that can automate the laborious process of running and linking the different models and datasets e.g. the Traffic Emission Modelling and Mapping Suite; TEMMS (Namdeo et al., 2002) can go a long way in speeding up similar work in the future and making it more feasible. Furthermore, many practical difficulties were faced during this work. The key ones are summarized in Figure 69, alongside general recommendations of who and how to deal with them.

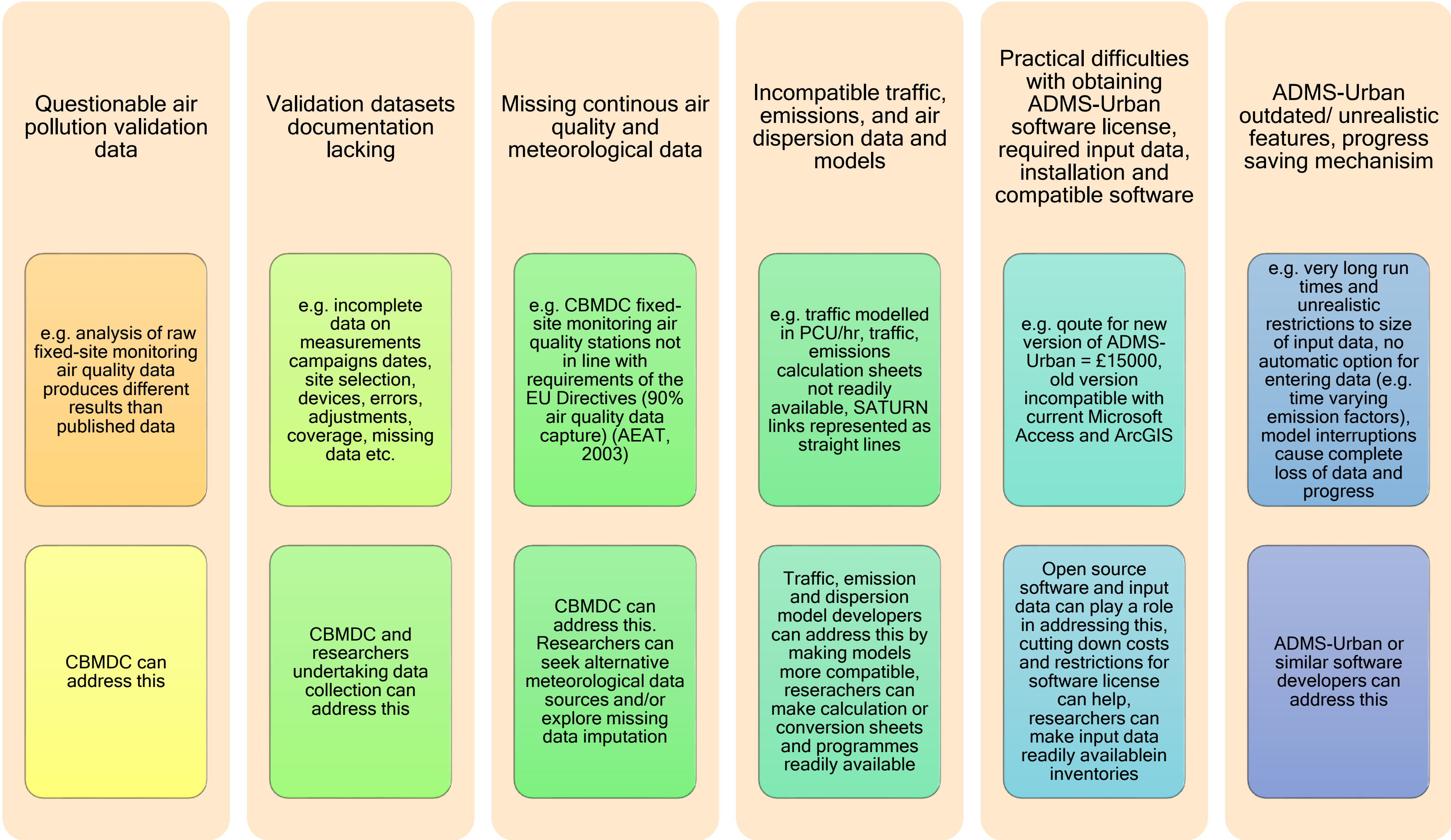


Figure 69 Key Practical Difficulties in Setting Up Full-Chain Exposure Models

5.5.2. Strengths and Comparison to other Studies

This work is one of few attempts to model the full-chain of TRAP linking a suite of traffic assignment, emissions, and dispersion models and characterizing the full-chain from exposure source (traffic activity), to source emissions (traffic emissions), to resulting air quality and exposures (emissions dispersion and air pollution levels) (Namdeo et al., 2002, Hatzopoulou and Miller, 2010, Wang et al., 2016a, Mitchell et al., 2005). The scarcity of full-chain exposure modelling is commonly attributed to the severity of data demands, the unavailability of required software/expertise and the complexity of linking various (incompatible) models which were originally developed independently (de Nazelle et al., 2011, Jerrett et al., 2005).

Despite these practical hurdles, which were indeed faced in this research study, full-chain exposure modelling is theoretically the most formal and detailed approach to predict air pollution levels and (changes in) exposures due to specific sources (Nieuwenhuijsen et al., 2017, de Nazelle et al., 2011). The traffic assignment, emissions and dispersion models used in this study are all well-established and have been validated in several studies, showing good agreement with real-world measured data which supports their use (see Section 3.3.3. for SATURN validation; 4.1.4. and 4.3.5. for COPERT and PHEM validation and 5.1.3. for ADMS-Urban validation). In this research study, the final outputs of the dispersion model were validated against the ESCAPE's 39 NO_x diffusion tube measurements (the only direct source of NO_x data) and the snapped models achieved an R^2 of 0.60 and 0.62 (Table 31). This was considered as good performance for the full-chain model and was comparable to validation in previous work e.g. R^2 of ADMS-Urban models ranging from 55%-91%; R^2 of a full range of dispersion models used in TRAP and asthma research ranging from 34%-88% (Khreis and Nieuwenhuijsen, 2017). This work added to the literature showing that different emission factors did not result in different model performance.

In line with the premise of the full-chain exposure modelling (Section 1.2.), this study has the key practical advantage of linking the estimated air pollution levels back to their specific sources giving a clearer idea of the contribution of different sources to overall air pollution levels. For example, the contribution of the different vehicle classes to the total transport NO_x emission inventories was estimated (Figure 58). These results highlight an important and a previously established sensitivity in emissions models' source apportionment with implications for air quality and health improvement policies. The standard COPERT functions suggested that diesel passenger cars, petrol passenger cars and HDVs, respectively, were the worst polluters whilst the new functions suggested that these were HDVs, diesel passenger cars and buses and coaches, respectively; shifting the emphasis from cars to HDVs. Only one similar study was found in the literature (Peace et al., 2004) which showed that between three different and successive sets of road traffic emission factors released by the UK government, the latest, and theoretically more accurate set (due to the larger database of emission measurements that it has been based on), estimated emissions for heavy and light good vehicles which were considerably higher than calculated using older sets. Linked to this point, a key addition to the literature was the development of new average-speed-emission functions and exploring their effects on total NO_x and source apportionment. Previous full-chain modelling only utilized existing emission models (Namdeo et al., 2002, Hatzopoulou and Miller, 2010, Wang et al., 2016a, Mitchell et al., 2005). The new average-speed-emission functions suggested that COPERT under estimates emissions at the lower speed ends and resulted in different source apportionment as shown in Figure 58 and Figure 59. The results at the lower speed ends, although eventually not influential on the models' results and performance, are relevant in populated urban areas where short links are abundant and stop-start driving is common. The fact that the final estimates and validation metrics did not notably differ based on the emission factors used is discussed below.

The comparison between the COPERT-based and the PHEM-based dispersion models, provided new insights that the difference in the final performance of these two methods is impacted by the SATURN speeds data (Figure 59 and Figure 63). At the lower average speeds, the differences between the COPERT-based and the PHEM-based emission functions were stark (Figure 59), yet when the dispersion modelling was undertaken, the impact of these differences was limited to a select number of receptor output points (Figure 63), and overall, the final results, and the subsequent burden of disease estimates (Section 6.4.1), were not impacted. This may be explained by the lack of road links with low average speeds. On the other hand, most road links had average speeds that would results in higher COPERT-based emission estimates (between 12 and 80 km/h), adding up and resulting in higher NO_x levels from the COPERT-based dispersion model, overall. These results would have been reversed, if more links were at the lower speed ends and/or the vehicle tracking survey (Chapter 4) was extended and leveraged PHEM-based emission functions at the higher speed ends (see Section 4.5.3.). This insight pinpoints a previously unrecognized point at the outset of this study: the (theoretical) improvements in the emission modelling stage *do not* result in overall improvements in air quality or burden of disease estimates. Overall improvements in air quality and burden of disease estimates are only likely when improvements in the emission modelling stage are coupled with improvements in the traffic modelling stage to better capture the roads with lower average speeds (and higher start-stop driving).

Further strengths were related to the use of theoretically more realistic site and meteorological parameters, which were not the default values in ADMS-urban (Table 21), to account for the effect the presence of buildings has on wind speeds (Stocker, 2015). The use of the varying background levels was also considered as an advantage in comparison to using constant background levels, which were unrealistic and resulted in worse model performance. Similarly, the use of the time varying emission factors based on hourly varying traffic levels and associated emissions (Figure 56) was considered as an advancement of previous practice (de Hoogh et al., 2014). Both COPERT and the newly developed average-speed-emission functions were applied in a very detailed manner considering 167 vehicles (sub-) classes. This is a much more detailed categorization than that (2 or 6 vehicle categories) built in ADMS-Urban (Cambridge Environmental Research Consultants Ltd, 2010) and is a more realistic representation of the vehicles variation within the Bradford's fleet.

Another addition to the literature was in the comparison of the LUR versus the dispersion models and the comparison of all the models' validation metrics against different validation datasets (Khreis et al., 2017a). Recent literature pertaining to these two points is limited (de Hoogh et al., 2014, de Nazelle et al., 2013, Beelen et al., 2010, Dijkema et al., 2011). Beelen et al. (2010) compared the performance of a 100 x 100 m grids LUR and dispersion model used to estimate NO_2 levels at 69,975 receptor output points in a large urban area in the Netherlands. Similarly to this study, Beelen et al. (2010) showed moderate correlations between NO_2 levels estimated from the LUR and the dispersion models (r = 0.55, compared to r = 0.47 with the PHEM-based model and 0.50 with the COPERT-based model in this study) and a large scatter in the relationship between the two models at the individual receptor output points. Unlike this study, the LUR model predicted higher concentrations at both the lower and higher end of the concentration range, and similar concentrations in the mid-range. Beelen et al. (2010) also showed that when the modelled concentrations were compared with measured concentrations at 18 independent validation sites, the dispersion model performed better than the LUR model with r =

0.77 compared to 0.47 for the LUR model. This observation was not confirmed in the current study where the validation performance was contingent on the validation dataset used and likely distorted by the SATURN links misplacement/ inaccurate geo-locations and the roads representation as straight lines (see Section 3.4.4.). In a similar exercise, de Hoogh et al. (2014) estimated NO_2 concentrations from a LUR and an ADMS-Urban dispersion model at 20,919 residential addresses in Bradford and found a better correlation between the two models' estimates (r = 0.67). The validation of the dispersion model against 40 ESCAPE tubes (1 influential site removed) resulted in a similar performance (r = 0.74) (de Hoogh et al., 2014) to that documented in this study (r= 0.78) (Table 31).

Linked to the relevance of the validation dataset selection demonstrated in Table 28, de Nazelle et al. (2013) showed that the performance of the ESCAPE LUR model is better when validated against (internal) measurements from the ESCAPE sites whilst the R^2 dropped by 17%-18% when the model was validated against external, independent measurements. A similar pattern was seen for LUR models developed in particular projects and applied to different external validation datasets. The worsening of performance was suggested to be due to a combination of over-fitting and differences in sampling protocols, specifically the sampling years and selection of monitoring sites (de Nazelle et al., 2013). Similarly, Dijkema et al. (2011) validated two NO_2 LUR models once against their internal datasets and once against the NO_2 dataset used to develop the other LUR model. The authors showed that both LUR models performed less well in predicting NO_2 concentrations at the external sites as the R^2 dropped by 22% and 24%. The results of this study are in line with these observations and also show that, similarly to the LUR models (Dijkema et al., 2011, Khreis et al., 2017a), the validation datasets selection impacts the validity parameters of the dispersion models too (Table 28).

5.5.3. Limitations

This study also has its limitations. The key limitations are those related to the use of the SATURN traffic model, namely due to its road links misplacement/ inaccurate geo-coding, the representations of roads as straight lines (Section 3.4.4.), the lack of speeds variability between the different simulation periods (Figure 25) and the congestion under estimation (Section 3.3.3.). These issues are discussed in turn.

First, the unrealistic lack of temporal variability of the speeds and lack of low speed driving data from the SATURN model (Steer Davies Gleave, 2009), was an issue of important relevance. For example, in the AM peak hour, only about 11% of all modelled links (497/4500) had an average speed ≤ 10 km/h; compared to about 10% (445/4500) in the inter-peak and about 12% (525/4500) in the PM peak hour (link-based speed). On the other hand, the real-world driving cycles were driven at speeds ≤ 10 km/h 41% of the time (instantaneous speed). This traffic modelling limitation inhibited the application of the new average-speed-emission functions in a meaningful manner (see Figure 63 and associated discussion). However, outlook is changing with emerging real-time telematics data which can be used in the future instead of coarsely resolved SATURN traffic information (Nyhan et al., 2016).

Second, the analyses and validation of the SATURN model data was only undertaken for traffic flows and the issue of the geo-locations inaccuracy was not fully appreciated until the dispersion modelling work started. The snapping method developed in this work (Section 3.4.4.) attempted to overcome some of these inaccuracies but was laborious, required multiple iterations until the final user-specific conditions were agreed on and selected. Due to the time restrictions of this study and the fact the SATURN model used was obsolete and was being updated by CBMDC, the snapping method was the best attempt for dealing with these issues. The snapped network improved the model's validity bringing its R^2 up by up to 12% (Table 30 and Table 31). However, the snapping method did not deal with the road links being represented as straight lines in the SATURN model. This issue is expected to have resulted in poorer validation as the distance between the roads (and their emissions and subsequent air pollution) and the validation sites where real-world NO_x was measured was inaccurate. Therefore, improvements in the SATURN network links' geolocations may further improve the dispersion models' validation performance.

Further limitations relate to the emission modelling stage. As shown in Table 24, for petrol passenger cars, COPERT estimated NO_x emissions that are > 50 % higher than the PHEM-based estimates. This difference was predominantly driven by the petrol EURO 0 passenger cars, whose data may be questionable due to the limited sample size available for older vehicle categories at the time of COPERT development and the possibility that vehicles tested under this category were of poor maintenance and/or failed catalysts. Furthermore, both COPERT and PHEM are emission models that are underlined by data collected from emission tests typically undertaken at temperatures between 20-30 °C (Keller et al., 2017). Emissions outside these temperature windows, specifically at low temperatures, are higher as NO_x controls are less effective (Weilenmann et al., 2009, Dardiotis et al., 2012, Westcott, 2016, Department for Transport, 2016b). This issue has not been controlled for and is likely to be part of the models under estimation (Figure 68) as temperatures in Bradford are clearly lower than the 20-30 °C window (9 °C on average).

Linked to both the traffic and the emission modelling stages, another limitation related to the use of constant vehicle proportions across all road links and all hours. In reality, the fleet composition differs on different streets types, e.g. rural, urban and highways, but also differs significantly within urban roads based on the locations and use of the roads and time of the day (Wyatt et al., 2016, AECOM Transportation, 2014). These differences can impact both vehicle emissions and TRAP levels estimated as different roads and time periods have different speeds (impacting emissions) and different meteorology (impacting TRAP).

There are further limitations which are inherent in the dispersion modelling itself. For example, meteorology at the exposure scale (100 x 100 m grid) is influenced by complex physical features including traffic turbulence which is difficult to consider. The models also tend to overestimate pollution levels during periods of calm wind (Khreis and Nieuwenhuijsen, 2017). Further, and due to the unavailability of more detailed data, the effects of buildings adjacent to roads (street canyons) were not considered and therefore the additional turbulent flow patterns occurring inside a street canyon and their effects on air quality were not take into account (Vardoulakis et al., 2003). However, as this option only affects results at output points inside the street canyons (and at heights below the height of the canyon) (Cambridge Environmental Research Consultants Ltd, 2010), it was not considered significant in the current study being a health impact assessment study where air pollution levels will be finally averaged at the census tract level (Chapter 6). The estimation of TRAP at a 100 * 100 m grid scales is also a limitation as TRAP can significantly vary at the scale of 10s of meters (Beevers et al., 2013).

Due to the absence of multiple background monitoring stations in Bradford which can provide variable NO_x background levels, the DEFRA background air pollution maps were used. These maps have low spatial and temporal resolution but were the only available option in this study and are the typical source of background data used in local air quality review and assessment (Sayegh et al., 2016), including by CBMDC. Overall, these background levels improved the performance of the dispersion models (Table 28), but they still may under estimate or not incorporate all sources of emissions as the NO_x measurements at the validation sites were generally higher than modelled NO_x (Figure 68). Higher resolved spatially varying background levels are currently lacking (Sayegh et al., 2016) but may improve the models' performance.

Another note should be made regarding the uncertainties associated with the validation data used in this study, especially in the diffusion tubes measurements (Table 22). When compared to continuous monitoring stations, NO_x diffusion tubes were previously shown to statistically significantly under estimate NO_x by 39.9% to 68.4%, and this was attributed to ineffective conversion of NO into NO_2 by the NO_x sampler, especially at high ambient concentrations (Vardoulakis et al., 2009). Therefore, the models under estimation may even be higher.

Finally, exhaust NO_x was the only pollutant modelled in this study and NO_2 concentrations were derived by conversion, using one average Bradford-specific NO_2/NO_x ratio (Section 5.3.5). A preferable alternative, which would have also impacted the TRAP variability and R^2, would have been to use spatially varying NO_2/NO_x ratios, depending on the location of the receptor data point in relation to the roads, e.g. using NO_2/NO_x ratios specifically for roads within 300 m buffers from roads and different ratios for urban background and rural areas. However, due to the issue with the SATURN links misplacement and their representation as straight lines, this option was ruled out as it was not possible to define meaningful and accurate buffers around roads, where e.g. road specific NO_2/NO_x can be applied.

5.5.4. Avenues for Future Work and Next Steps

Future work can explore the impacts of using different fleet mix (e.g. by road type, area, time of the day) on the modelling results and validation. The under estimation of congestion is a relevant issue and future work can benefit from improved traffic modelling or further calibration using comprehensive speed measurements. SATURN can be used to model traffic flows and speed values for hours outside the 3 typical simulation periods (AM, inter-peak and PM peaks) (Gulliver and Briggs, 2005). Beyond improving modelling, traffic flows and speeds may be obtained from observed data e.g. telematics (Pellecuer et al., 2016, Nyhan et al., 2016). The impact of cold start emissions on air pollution concentrations and different NO_2/NO_X ratios based on distance from the road and location should be further explored. The reasons behind the dispersion models under estimation warrants further in-depth research which for e.g. can focus on smaller parts of the road network and iteratively model and validate air pollution levels using differing traffic flows and fleet mixes (e.g. using local fleet mix), emission rates (e.g. lifted emission rates), speeds (higher congestion) and roads with more accurate locations and curvatures. The next steps of this study will assign exposures from the LUR and the two dispersion models to the census tract area level and estimate the associated burden of onset childhood asthma in Bradford.

6 Health Impact Assessment

6.1. Background

6.1.1. Burden of Disease and Health Impact Assessment

It has been long recognized that public health is influenced by actions and policies outside the healthcare sector including land-use, transport, housing, and industry (Mindell et al., 2003). In recent years, the impacts of the transport sector on public health have been gaining increasing attention in academic and policy circles (Khreis et al., 2016, Mindell, 2017, World Health Organization, 2011). To systematically assess and quantify these impacts, many countries and cities are increasingly using Burden of Disease (BoD) and Health Impact Assessment (HIA) methods (Herriott and Williams, 2010, Dannenberg et al., 2008). BoD and HIA studies can identify public health impacts including the health risks and benefits of current and proposed transport plans or policies (Nieuwenhuijsen et al., 2017). The results of BoD and HIA are easy to grasp and therefore relevant for public health professionals, policy makers and the public. They are often presented to policy makers to aid their decision making and/or to the public to catalyse their understanding of health determinants (Bhatia, 2010, Birley, 1995, Lock, 2000, Douglas et al., 2001, Mindell et al., 2003, Künzli et al., 2008).

BoD and HIA are terms which have been used interchangeably, but there are subtle differences between these two methods. BoD studies asses the contribution of a risk factor e.g. levels of air pollution to the burden of disease in a specific context/study area. This is done by calculating the fraction of disease or death in the population, attributable to the risk factor under investigation (Vander Hoorn et al., 2004). On the other hand, HIA is described as *‘a combination of procedures, methods and tools by which a policy, program or project may be judged as to its potential impacts on the health of a population, and the distribution of those impacts within the population’* (World Health Organization, 1999). HIA is a method for assessing *the changes* in health risks or benefits i.e. health impacts attributable to a plan (project, program) or policy in the non-health sector. In brief, the difference between a BoD and a HIA is in whether scenarios comparing different exposures are investigated: HIA includes a scenario that results in changes in health risks or benefits whilst BoD only quantifies the burden of disease attributable to a risk factor (or an implicit scenario of eliminating the risk factor, e.g. reducing air pollution exposure levels to zero or a ‘safe threshold’).

Whilst BoD studies are, in nature, quantitative, HIA studies can be quantitative and/or qualitative. The most common HIA studies, especially in policy and practice circles, are qualitative, relying on qualitative evidence, social sciences, expert opinion and stakeholder knowledge to only identify the range of the health determinants associated with a plan or policy and the direction of the health impacts (i.e. whether these are risks or benefits) (Mindell et al., 2003, Nieuwenhuijsen et al., 2017, Khreis et al., 2017e, Herriott and Williams, 2010).

HIAs can also include a quantitative assessment adopting a comparative risk assessment approach, by investigating the health impacts of different (positive and negative) exposures, across different scenarios (Briggs, 2008). Both BoD and HIA, when quantitative, can provide numeric indices of health risk factors, inform the health benefit/risk trade-off of public policies (Mueller, 2017), and provide the basis for other economic evaluations such as cost-benefit analyses (World Health Organization, 2015, Mueller, 2017). This facilitates and adds defensibility to the inclusion of health in public policy. Undertaking a quantitative HIA combines several steps including:

1) defining the exposure(s) of interest, exposure(s) measures and ranges;
2) defining the health outcome(s) of interest associated with the exposure(s) and their frequency (incidence) amongst the exposed population;
3) selecting exposure-response functions (risk estimates) to quantify the strength of association between selected exposure(s) and selected health outcome(s);
4) combining exposure(s) data with population data and exposure-response functions to quantify the attributable proportional health burden of the health outcome of interest and;
5) quantifying the uncertainty in the estimated health burden (range of potential effects) (Perez et al., 2009, World Health Organization, 2015).

Often and preferably, the exposure-response functions are sourced from systematic reviews and meta-analyses, as these are considered as the best available and generalizable evidence; in the common absence of exposure-response functions specific to the local populations of interest (Nieuwenhuijsen et al., 2017).

6.1.2. Literature Review and Research Gaps

The number of BoD and quantitative HIA studies of transport related risk factors has been increasing and many of which estimate the impacts of air pollution

(Nieuwenhuijsen et al., 2017). The largest BoD study to date is the Global Burden of Disease (GBD) study which contains health impact estimates, in terms of attributable deaths, years of life lost (YLLs), years lived with disability (YLDs) and disability-adjusted life year (DALYs), of 79 behavioural, environmental and occupational, and metabolic risks, produced at national or regional levels in 188 countries (Forouzanfar et al., 2015). The GBD study estimated that physical inactivity and ambient air pollution, combined, cause > 5 million annual premature deaths. The contribution of transport to this burden was not specified. In another BoD study by Lelieveld et al. (2015), the contribution of transport to premature mortality was defined as land transport emissions were estimated to cause 1/5 of all deaths attributable to $PM_{2.5}$ and O_3 in Germany, the UK and USA whilst globally, they were estimated to cause 5% of premature deaths (Lelieveld et al., 2015).

Until now, estimates of BoD have been mainly produced on a national or regional scale (Mueller et al., 2017). Although insightful, air pollution BoD estimates at a global, regional and national level, as above, are less useful for local authorities. At a local scale, averaged impacts over larger populations are not adequate to evaluate health impacts from local risk factors and the impacts of local interventions (Perez et al., 2009, Nieuwenhuijsen et al., 2017). With cities moving to the forefront of providing solutions for environmental and health issues (Gouldson et al., 2015), BoD/HIA estimates at a local level are valuable to demonstrate health impacts of current and proposed policies. Local BoD/HIA also offer the potential to engage with the affected communities, catalyse their understandings of health determinates and provide them with information to help them better evaluate current and proposed policies (Van Brusselen et al., 2016, Nieuwenhuijsen et al., 2017, Ringland, 2017). BoD and HIA studies for cities are relatively new and lack full-chain models (Nieuwenhuijsen et al., 2017). These studies, as in traditional HIA, have generally been focused on premature mortality and the quantification of TRAP's impact on morbidity is less developed (Künzli, 2002, Künzli et al., 2008).

Of relevance is the impact of TRAP on the development of childhood asthma. Little work has been undertaken to estimate the burden of childhood asthma attributable to TRAP. Only four relevant studies, coming from the same group, were identified in the literature (Perez et al., 2009, Perez et al., 2013, Künzli et al., 2008, Perez et al., 2012). The key elements of these studies are summarized in Table 33 and overviewed next. Three of these studies were conducted in California, Long Beach, Riverside and Los Angeles county (Künzli et al., 2008, Perez et al., 2009, Perez et al., 2012). The fourth study was conducted in 10 European cities (Perez et al., 2013) (Table 33). All four studies estimated the impacts of exposure to TRAP, characterized by proximity to major roadways, on asthma prevalence in children between birth and 18 years old. Baseline childhood asthma prevalence rates in the four studies was similar at around 12% in most areas, but different in the Perez et al. (2013) study in the cities of Bilbao and Ljubljana (21.3% and 29.2%); Brussels (7.3%); Stockholm (9.3%) and Vienna (5.8%). In all four studies, the asthma prevalence exposure-response function was sourced from an individual estimate in a Southern Californian population-based study by McConnell et al. (2006) who estimated that the risk of prevalent asthma associated with long term residence of < 75 m from a busy road is 1.64 (1.10, 2.44), in children aged 5-7 years. Overall, these studies suggested that 6% to 14% of childhood asthma cases were attributable to TRAP exposure; as characterized by traffic proximity.

These studies, despite pioneering in studying asthma as a morbidity outcome in TRAP-HIA, have important limitations which are summarized in Table 33 and which will be addressed in the present work. First, these studies are relying on residential proximity to major roadways as the TRAP exposure metric. Proximity to major roadways is a crude exposure measure which is sensitive to confounding by socioeconomic factors, cannot provide information on the impacts of specific sources and actual pollutants and lacks consideration of significant local emissions and dispersion processes (Beevers et al., 2013, Khreis and Nieuwenhuijsen, 2017).

Second, the exposure-response function used in these studies was sourced from an individual study rather than a meta-analysis. This can be argued as preferable in the Southern Californian HIA studies (Künzli et al., 2008, Perez et al., 2009, Perez et al., 2012), where the exposure-response function come from, but not in the European study (Perez et al., 2013). The use of the point exposure-response estimate resulted in large statistical uncertainty around the estimated burden but at the time, there were no meta-analytical exposure-response functions available which could be used.

Third, the age range for which the exposure-response function related to and the age range of the population under study did not match, something which could impact final estimates (Table 3). Uncertainties in health impact estimates due to uncertainties in the exposure assessments and the underlying health outcome estimates have not been examined and are issues which are generally underexplored in the literature.

Finally, these studies examined prevalent asthma, rather than incident asthma, defined as '*the reported use of controller medications for asthma in the previous year or (physician) lifetime asthma with any wheeze in the previous year. In addition,* *children without a physician's diagnosis who had severe wheeze in the previous 12 months were included as prevalent asthmatics to identify asthma undiagnosed because of poor access to medical care*" (McConnell et al., 2006). Therefore, these studies do not give indication of how many asthma cases could be avoided.

Table 33 Main Characteristics of HIA Studies on TRAP and Childhood Asthma

Study	Künzli et al. (2008)	Perez et al. (2009)
Setting	California, Long Beach	Southern California, Long Beach and Riverside
Age group (years)	Children aged 0-17 years	Children aged 0-17 years
Exposure assessment	Distance to the nearest major road defined as an interstate freeway, US highway or limited access highway, or other highway or arterial roads, monitoring data for NO_2	Proximity to major roadways (distance from major roads to households assigned to grids), monitoring data for NO_2 and O_3
Pollutant(s)	Living near a busy road, NO_2	Living near a busy road, NO_2, O_3
Outcome(s)	Episodes of bronchitis symptoms, **asthma prevalence**	Bronchitis episodes among those with asthma, clinic visits for asthma, emergency department visits for asthma, hospital admissions for asthma, **asthma prevalence** (attributable to living < 75 m from a busy road)
Source of exposure-response functions	Individual local study: McConnell et al. (2006) (asthma prevalence associated with living < 75 m from a busy road)	Individual local study: McConnell et al. (2006) (asthma prevalence associated with living < 75 m from a busy road)
Exposure-response function (95% CI)	1.64 (1.10, 2.44) – for age 5-7 years	1.64 (1.10, 2.44) – for age 5-7 years
Baseline childhood asthma rates	Asthma prevalence: 12.8%	Asthma prevalence in Long Beach: 12.8% Asthma prevalence in Riverside: 14.9%
Tested scenarios	Numbers of children living in the first 75 m of busy roads is reduced to zero or high TRAP along busy roads would fall to levels in areas > 75 m of busy road	• No ship emissions • NO_2 levels reduced to levels in the cleaner coastal southern Californian communities (11 and 18 ppb reductions) • Numbers of children living in the first 75 m of busy roads is reduced to zero or high TRAP along busy roads would fall to levels in areas > 75 m of busy road
Limitations as reported by the authors	• Assuming that TRAP develops asthma (at the time only emerging evidence) • The use of an exposure-response function from a single rather than a pooled estimate which caused large statistical uncertainty (at the time enough studies for the derivation of a meta-analytical estimate were unavailable) • Using traffic proximity as a proxy for exposure to TRAP and the attribution of uniform risk to children at all residential distances within 75 meters of a major roadway (a simplification of the continuous decline to approximately 200 meters) • Age range for exposure-response function and the population under study did not match • Population attributable fraction considers one risk factor at a time (not a multi-causal model)	• Assuming that TRAP develops asthma (at the time only emerging evidence) • The use of an exposure-response function from a single rather than a pooled estimate which caused large statistical uncertainty (at the time enough studies for the derivation of a meta-analytical estimate were unavailable) • Using traffic proximity as a proxy for exposure to TRAP and the attribution of uniform risk to children at all residential distances within 75 meters of a major roadway (a simplification of the continuous decline to approximately 200 meters) • Age range for exposure-response function and the population under study did not match • Population attributable fraction considers one risk factor at a time (not a multi-causal model)
Relevant findings	1626 cases of childhood asthma in Long Beach (9.3% of all cases) were attributable to traffic proximity. Substantial impact of traffic proximity on asthma exacerbation (up to 39.8% of all exacerbations)	1600 cases of childhood asthma in Long Beach (9% of all cases) and 690 in Riverside (6% of all cases) were attributable to traffic proximity. Substantial impact of traffic proximity on asthma exacerbation e.g. up to 55% of all bronchitis episodes

Study	Perez et al. (2012)	Perez et al. (2013)
Setting	California, Los Angeles County	10 European cities, Barcelona, Bilbao, Brussels, Granada, Ljubljana, Rome, Sevilla, Stockholm, Valencia, Vienna
Age group (years)	Children < 18 years old	Children aged 0-17 years
Exposure assessment	Proximity to busy roads, monitoring data for NO_2 and O_3	Proximity to busy roads, defined as roads with >10,000 vehicles / day (distance from major roads to households assigned to grids), monitoring data for NO_2 and PM_{10}
Pollutant(s)	Living near a busy road, urban NO_2 and O_3	Living near a busy road, urban NO_2 and PM_{10}
Outcome(s)	**Asthma prevalence** (attributable to living < 75 m from a busy road), asthma exacerbations including bronchitis episodes, doctor visits, emergency department visits, hospital admissions, school absence for respiratory illness	**Asthma prevalence** (attributable to living < 75 m from a busy road), asthma exacerbations, symptoms, hospital admissions
Source of exposure-response functions	Individual local study: McConnell et al. (2006) (asthma prevalence associated with living < 75 m from a busy road)	Individual study: McConnell et al. (2006) (asthma prevalence associated with living < 75 m from a busy road)
Exposure-response function (95% CI)	1.64 (1.10, 2.44) – for age 5-7 years	1.64 (1.10, 2.44) – for age 5-7 years

Baseline childhood asthma rates	Asthma prevalence: 12.6%	Asthma prevalence in Barcelona: 11.8% Asthma prevalence in Bilbao: 21.3%; Brussels: 7.3%; Granada: 12.6%; Ljubljana: 29.2%; Rome: 12.6%; Seville: 13.0%; Stockholm: 9.3%; Valencia: 11.0%; Vienna: 5.8% Average in 10 cities: 12.8%
Tested scenarios	• A reduction in annual concentrations of regional pollutants for each census block group to levels found in clean communities (from 23.3 ppb to 4 ppb for NO_2 and 39.3 ppb to 36.3 ppb for O_3) in combination with a reduction in the proportion of children in the county living within 75 m of a major road from 17.8% (current) to 0% • A 20% reduction in the annual concentrations of regional pollutants for each census block group (from 23.3 ppb to 19.4 ppb for NO_2 and 39.3 ppb to 38.7 ppb for O_3) in combination with a 3.6% reduction in the proportion of all children in the county living within 75 m of a major road (from 17.8% to 14.2%, corresponding to a 20% decrease in the proportion of children currently living within 75 m) • A 20% reduction in regional pollutant concentrations in combination with a 3.6% increase in the proportion of children living within 75 m of a major road (from 17.8% to 21.2%).	• Numbers of children living in the first 75 m of busy roads is reduced to zero
Limitations as reported by the authors	• Using traffic proximity as a proxy for exposure to TRAP • Assuming that TRAP develops asthma (at the time only emerging and uncertain evidence) • Population attributable fraction considers one risk factor at a time (not a multi-causal model) • The time lag that might be required for health benefits to be achieved was not addressed • Not accounting for additive effects of different pollutants • The use of an exposure-response function from a single rather than a pooled estimate (at the time enough studies for the derivation of a meta-analytical estimate were unavailable) • Only accounting for exposures at the home address and not at the school addresses • Under-diagnosis of asthma may mean that prevalence used to derive attributable cases was too low • Exposure to TRAP along smaller streets has been ignored • Other health outcomes associated with air pollution were not investigated	• Assuming that TRAP develops asthma (at the time only emerging evidence) • Population attributable fraction considers one risk factor at a time (not a multi-causal model) • The use of an exposure-response function from a single rather than a pooled estimate (at the time enough studies for the derivation of a meta-analytical estimate were unavailable) • Under-diagnosis of asthma may mean that prevalence used to derive attributable cases was too low • Population exposure to TRAP along smaller streets have been ignored • Using traffic proximity as a proxy for exposure to TRAP
Relevant findings	2% (5,9000) to 12% (39,800) of all cases of childhood asthma could be prevented, depending on the scenario tested. One scenario could increase asthma cases by 2% (reduction in regional pollutant concentrations in combination with an increase in the proportion of children living within 75 m of a major road)	33200 cases of childhood asthma across the 10 cities (14% of all cases) were attributable to traffic proximity. Substantial impact of traffic proximity on asthma exacerbation e.g. up to 15% of all acute events

6.2. Chapter Objectives and Contribution to Literature

The objective of this research phase was ***to link TRAP exposure data to childhood population data and estimate the annual number of childhood asthma cases (from birth to 18 years old) attributable to TRAP exposures in Bradford, UK.*** *Another objective of this research phase was* ***to explore the impact of using different exposure assessment methods on the estimated number of childhood asthma cases attributable to TRAP and the sensitivity of the results to the underlying health outcome frequency estimates.*** As such, this research phase filled some of the literature gaps by moving beyond HIA and BoD studies mainly focused on premature mortality; estimating the morbidity burden of an outcome with significant healthcare and quality of life consequences. This research phase also contributed to overcoming some of the gaps associated with the current evidence base namely, the scarcity of city-level and full-chain BoD and HIA and the under-exploration of uncertainties associated with exposure assessments.

6.3. Methods

6.3.1. Exposure Modelling and Exposure Reduction Scenarios

Three exposure assessment models were used in this research study including 2 full-chain exposure assessment models covering the whole chain of traffic activity (Chapter 3), traffic emissions (Chapter 4) and air pollution dispersion (Chapter 5) and employing two distinct emission models. The third exposure model was a LUR model developed in the ESCAPE project and described in full in Beelen et al. (2013) (for NO_2 and NO_x) and Eeftens et al. (2012) (for BC, $PM_{2.5}$ and PM_{10}). In brief, the LUR method is a commonly used empirical method in air pollution epidemiology that uses least squares regression to combine measured pollutant concentrations with GIS-based predictor data reflecting pollutant sources and surrounding land use characteristics to build a prediction model applicable to non-measured locations (Khreis and Nieuwenhuijsen, 2017). NO_2 and NO_x LUR models were developed for Bradford from measurements overviewed in Section 5.3.5. and validated in 2012 as part of the ESCAPE project (Beelen et al., 2013). BC, PM_{10}, and $PM_{2.5}$ models were developed for London/Oxford and validated in 2012 as part of the ESCAPE project (Eeftens et al., 2012). These models were assumed to apply to Bradford and the LUR equations developed for London/Oxford were used in this research study. Similarly, they have been used to estimate air pollution levels in Bradford in previous publications (Pedersen et al., 2013, Schembari et al., 2015).

To construct air pollution maps, all three models were used to generate exposure estimates at 46,452 specified output points; each of which represented the centroid of a 100*100 m grid (as detailed in ‘Output Points (Grids Data)’, Section 5.3.3.). The exposure estimate at each of these points was held constant for all other points within (the whole of) each 100*100 m grid.

As an exposure reduction scenario to compare the estimated BoD to, air pollution was assumed to be reduced to zero. This, of course, is an unrealistic scenario, the aim of which was not to assess the impact of a plausible policy *per se* but rather to estimate the overall number of asthma cases attributable to TRAP and generate a BoD estimate (Section 6.1.1.). As another more plausible exposure reduction scenario, air pollutants at each census tract which was exceeding the WHO Air Quality Guideline values (Krzyzanowski and Cohen, 2008), were reduced to comply with the guidelines. This scenario was applicable to three pollutants:

- NO_2 reduced to 40 µg/m^3 (annual average)
- PM_{10} reduced to 20 µg/m^3 (annual average)
- $PM_{2.5}$ reduced to 10 µg/m^3 (annual average)

The reduction in new asthma cases attributable to these scenarios was calculated, although these estimates are only indicative as there is no evidence that health effects do not occur under these thresholds (Health Effects Institute, 2010).

6.3.2. Population Exposure Distribution

The ‘output area’ was the lowest geographical level at which census population data were available (Office for National Statistics, 2016). This was the geographical level used to assign childhood population data, exposure data, attributable fraction and attributable cases. The characteristics of Bradford’s output areas are in Table 34.

Table 34 Characteristics of Bradford’s Census Output Areas

Number of output areas	1,528 output areas
Total number of children in all output areas (birth – 18 y.o.)	143,472 children
Average number of children in all output areas (birth – 18 y.o.)	94 children
Minimum number of children in an output area (birth – 18 y.o.)	3 children
Maximum number of children in an output area (birth – 18 y.o.)	468 children
Percentage of children ≤ 6 years old (pre-school age) in all output areas	44.7%
Percentage of children > 6 years old (school age) in all output areas	55.3%

Average area of all output areas (m^2)	239,802
Minimum area of an output area (m^2)	3,817
Maximum area of an output area (m^2)	15,395,650

There were 1,528 output areas in which a total of 143,472 children lived (year 2011). The digital boundaries of the output areas were extracted from the UK Data Service: 'Boundary Data Selector' (https://borders.ukdataservice.ac.uk/). The childhood population and age data were extracted from the UK Data Service: 'InFuse' (http://infuse.ukdataservice.ac.uk/). The 2011 census data were used as these were considered more compatible with the 2009 exposure estimates than the 2001 census data; the only other dataset available. The childhood population data within the output areas' digital boundaries is shown in Figure 70. Most children lived in the areas within and around the Ring Road; in the South East of Bradford.

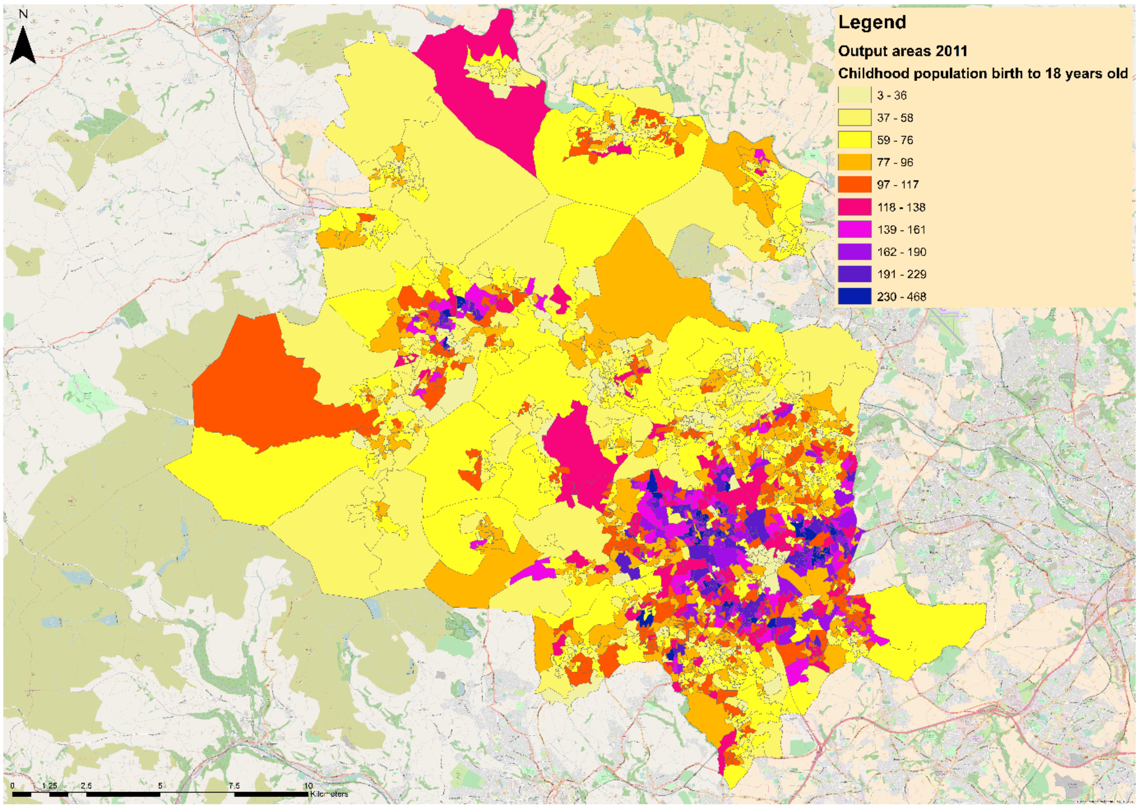


Figure 70 Output Areas Digital Boundaries and Childhood Population (Birth to 18 Years Old), Source: Own Work (Arc Map 10.4), Data Source: Office for National Statistics (2011)

The census tracts' average annual exposure levels for the different pollutants studied and from the 3 different exposure assessment models were obtained by intersecting the air pollution maps with the underlying census maps and summarizing the raster cell values (from the air pollution maps) contained within each underlying census tract/polygon (using the ‘isectpolyrst’ tool in the Geospatial Modelling Environment suite version 0.7.4.0.).

Where there was no intersection between the raster air pollution layers and the polygon boundaries (i.e. no underlying air pollution estimate because the census coverage was larger), these polygons were excluded from the analysis. The number of such polygon were 156(/1,528). In these areas, 10,089(/143,472) children, or ≈ 7%, of all children between birth and the age of 18 years lived. Therefore, this exclusion is expected to under estimate the burden of childhood asthma attributed to air pollution in Bradford.

6.3.3. Baseline Childhood Asthma Incidence Rates

The incidence rate of asthma in children from birth to 18 years old in Bradford was not found in the peer reviewed or the grey literature. Instead, the national incidence rate of childhood asthma (birth to 18 years old) in the UK was used. This was extracted from Punekar and Sheikh (2009) who reported 137 clinician-diagnosed asthma cases per 10,000 person-years, by the age of 18 years, as identified for 43,473 children indexed in the General Practice Research Database (GPRD).

In another Bradford specific publication, Mebrahtu et al. (2015) identified asthma, based on diagnostic and prescription codes in the primary care database, in 13,734 children aged 0 to 7 years, participating in the Born in Bradford cohort (Wright et al., 2013). Using the data reported in this paper, an asthma incidence rate of 123 per 10,000 person-years, by the age of 7 years, was calculated. However, and as the authors note, this figure is likely to be conservative due to the asthma diagnosis difficulties in this age range (Mebrahtu et al., 2015). Indeed, Bradford is known to have childhood asthma rates higher than national and regional averages (Yorkshire and Humber Public Health Observatory, 2012). Hence, Mebrahtu et al. (2015) also established another outcome termed ‘wheezing disorders based on treatment’ which identifies the existence of at least two drug prescriptions indicated for the treatment of asthma a minimum of 1 week and a maximum of 12 months apart. Based on this outcome, an asthma incidence rate (‘based on treatment’) of 442 per 10,000 person-years, by the age of 7 years, was calculated. Both incidence rates calculated from Mebrahtu et al. (2015) were used in sensitivity analyses to explore the influence of the background incidence rates in the impact assessment (Künzli, 2002).

6.3.4. Exposure-Response Functions

Exposure-response functions were extracted from the meta-analyses undertaken in this research study (Chapter 2). The 'overall' (birth to 18 years old) exposure-response functions for each pollutant were used (Table 3). The risk estimates for asthma development from these exposure-response functions had to be scaled to the difference in exposure between the reference (2009) average exposure level at each census tract and the two investigated exposure reduction scenarios (Section 6.3.1.):

- Scenario #1: air pollution reduced to zero; and
- Scenario #2: where exceeding the guidelines, air pollution reduced to the WHO Air Quality Guideline value (applicable to NO_2, PM_{10} and $PM_{2.5}$ only).

To scale a risk estimate to the exposure difference between the reference and the counterfactual scenarios, standard methods were used (Mueller et al., 2016), where:

$$RR_{exposure\_difference} = e^{\left(\left(\frac{\ln RR}{E_{RR\_unit}}\right)\times E_{exposure\_difference}\right)} \quad \ldots (Equation\ 6.1.)$$

Where RR is the relative risk obtained from the exposure-response function;
E_{RR_unit} is the exposure unit that corresponds to the RR obtained from the exposure response function;
$E_{exposure\_difference}$ is the difference in the exposure level between the counterfactual scenario and the reference scenario;
$RR_{exposure\_difference}$ is the scaled relative risk that corresponds to the difference in exposure level between the counterfactual (no exposure) and reference (2009 exposure) scenario

6.3.5. Population Attributable Fraction and Number of Cases

The population attributable fraction (PAF) is the proportional health burden of the health outcome of interest that is attributable to the difference in exposure level between the exposure reduction and the reference scenario (Murray et al. 2004; Vander Hoorn et al. 2004). PAF is a standard metric used in BoD and HIA studies and can be calculated as follows (World Health Organization, 2015):

$$PAF = \frac{\sum_{i=1}^{n} P\,(RR_{exposure\_difference} - 1)}{\sum_{i=1}^{n} P\left(RR_{exposure\ difference} - 1\right) + 1} \quad \ldots (Equation\ 6.2.)$$

Where P is the proportion of the exposed population;

$RR_{exposure\_difference}$ is the previously scaled RR that corresponds to the difference in exposure level between the counterfactual (no exposure) and reference (current exposure) scenario

n is the number of exposure levels

Finally, the number of childhood asthma cases attributable to the excess exposure:

$$\text{Attributable number of cases} = \text{PAF} * \text{expected cases due to all causes} \ldots \text{(Equation 6.3.)}$$

Where $\text{Expected cases due to all causes} = \text{childhood population} * \text{childhood incidence rate} \ldots \text{(Equation 6.4.)}$

An example for the BC calculations at census tract #E00053577 is given below (Table 35). These calculations were undertaken for each census tract, and each pollutant, separately. These results in Table 35 mean that in census tract # E00053577, 0.40 childhood asthma cases were estimated to be attributable to the BC annual mean exposure in that census tract.

Table 35 Calculation Example at one Census Tract for Black Carbon

Overall risk estimate per 0.5 x 10^{-5} m^{-1} BC = 1.08 (95% CI; 1.03, 1.14) (Table 3)

Census tract ID #	**E00053577**
Current annual average BC * 10^{-5} m^{-1} (from LUR model)	1.81
Counterfactual annual average BC * 10^{-5} m^{-1} – scenario #1	0
Exposure difference in 10^{-5} m^{-1} – scenario #1	1.81* 10^{-5} m^{-1} – 0 * 10^{-5} m^{-1} = 1.81 10^{-5} m^{-1}
Risk estimate $_{\text{exposure difference}}$ – scenario #1 (Equation 6.1.)	1.32
PAF – scenario #1 (Equation 6.2.)	0.24
Population (birth to 18 years old)	119
All-cause expected childhood asthma cases (incidence rate 137 per 10,000 person-years) (Equation 6.4)	119* 137/10,000 = 1.63
Attributable number of childhood asthma cases (Equation 6.3)	0.24*1.63 = 0.40
Counterfactual annual average BC * 10^{-5} m^{-1} – scenario #2	NA, no air quality guideline

6.4. Results

The annual average census tract pollutant levels, as estimated from the three exposure assessment models (Section 6.3.1.), are shown in Table 36. On average, these levels were low and the LUR model estimated higher NO_2 and NO_x than the full-chain exposure models. The annual average census tract pollutant levels were highly correlated with each other, with correlation coefficients ranging between 0.94 (for NO_2 (LUR) and NO_x (LUR)) to 0.40 (for NO_2 (snapped COPERT) and BC (LUR)). The correlation matrix showing the relationships between the different pollutant and model combinations can be found in Annex 6.1, Figure 72.

Table 36 Annual Average Census Tract Pollutant Levels (µg/m^3 for all pollutants except BC 10^{-5} m^{-1})

Statistic	Minimum	1stquartile	Median	Mean	3rd quartile	Maximum
NO_2 (snapped COPERT)	6.45	11.34	14.72	15.41	17.98	45.62
NO_2 (snapped PHEM)	6.40	11.23	14.41	15.21	17.65	55.19
NO_2 (LUR)	12.42	20.15	21.63	21.93	23.7	37.09
NO_x (snapped COPERT)	10.75	18.90	24.53	25.68	29.97	76.03
NO_x (snapped PHEM)	10.67	18.71	24.02	25.35	29.41	91.99
NO_x (LUR)	0.00	31.29	35.22	35.60	40.28	73.32
$PM_{2.5}$ (LUR)	7.67	9.62	10.31	10.40	10.97	26.13
PM_{10} (LUR)	12.17	15.54	16.53	16.63	17.65	27.94
BC (LUR)	0.85	0.90	0.99	1.07	1.16	3.60

6.4.1. The Impact of the Vehicle Emission Factors

The asthma cases attributable to NO_2 and NO_x as estimated from the two full-chain exposure models: the COPERT-based and the PHEM-based dispersion models are shown in Table 37. The use of the different emission factors in the two dispersion models (COPERT- and PHEM-based), differently from what was hypothesized at the outset of this study, did not have a significant impact on the final health burden estimated (Table 37). Using the COPERT-based dispersion model, the results suggested that, per year, 321 (range = 139, 428) asthma cases, or 18% of asthma cases attributable to all causes, were attributable to NO_2 in Bradford whilst 530 (range = -201, 976) annual cases, or 29% of all cases, were attributable to NO_x, the latter was not statistically significant. The estimates were similar to the PHEM-based dispersion model estimates (Table 37). There were no differences between the health impacts estimated using the original (unsnapped) (Annex 6.2.) and the processed (snapped) SATURN traffic network (Table 37).

In line with the premise of the full-chain exposure models developed in this work (Section 1.2.), additional analysis was undertaken to detangle the impact of TRAP from the impact of other air pollution sources. The results are shown in the last column of Table 37 (highlighted in light green) and suggest that the TRAP component of the overall air pollution models, as estimated using the two dispersion models, is only responsible for a small percentage of the air pollution attributable asthma cases; 3% for traffic-NO_2 and 5%-6% for traffic-NO_x. These estimates are likely to be an under estimation as discussed and demonstrated in Section 6.5.3.

Table 37 Estimated Annual Attributable Asthma Cases in Bradford using the Snapped COPERT- and PHEM-based Dispersion Models (*baseline asthma incidence = 137 per 10,000 person-year, baseline asthma incident cases = 1827*)

Model	Pollutant	Attributable cases	Attributable cases lower CI	Attributable cases upper CI	Percentage of all cases	Attributable cases to traffic
Snapped COPERT	NO_2	**321**	139	428	**18%**	**62 (3%)**
Snapped COPERT	NO_x	**530**	-201	976	**29%**	**109 (6%)**
Snapped PHEM	NO_2	**317**	137	423	**17%**	**57 (3%)**
Snapped PHEM	NO_x	**523**	-198	966	**29%**	**100 (5%)**

6.4.2. The Impact of the Exposure Assessment Method and the Pollutant Selection

The asthma cases attributable to NO_2 and NO_x as estimated from the third exposure model, the LUR model, are shown in Table 38. Also in the table are the asthma cases attributable to the LUR's estimates of the other pollutants: $PM_{2.5}$, PM_{10} and BC. The use of the LUR models, instead of the full-chain exposure models, had a significant impact on the health burden estimated, as did the selection of different pollutants.

Table 38 Estimated Annual Attributable Asthma Cases in Bradford using the LUR Models (*baseline asthma incidence = 137 per 10,000 person-year, baseline asthma incident cases = 1827)*

Pollutant	Attributable cases	Attributable cases lower CI	Attributable cases upper CI	Percentage of all cases
NO_2	**435**	191	573	**24%**
NO_x	**687**	-279	1196	**38%**
$PM_{2.5}$	**488**	182	732	**27%**
PM_{10}	**612**	279	866	**33%**
BC	**279**	113	447	**15%**

Using the LUR model, the results suggested that, per year, 435 (range = 191, 573) asthma cases, or 24% of all asthma cases, were attributable to NO_2 whilst 687 (range = -279, 1196) annual cases, or 38% of all cases, were attributable to NO_x, although the latter was not statistically significant (Table 38). As such, compared to the full-chain exposure models (Table 37), the LUR models resulted in 6%-9% higher attributable asthma cases. The LUR results also differed noticeably depending on which pollutant was used in the analysis with the highest asthma attributable cases related to NO_x (38%; although this was not statistically significant), followed by PM_{10} (33%), $PM_{2.5}$ (27%), NO_2 (24%) and finally BC (15%) (Table 38).

6.4.3. The Impact of the Exposure Reduction Scenario

Table 36 shows that average air pollution levels estimated from the three exposure models were low. There were 6 of 1,528 census tracts which exceeded the annual WHO air quality guideline of 40 µg/m^3 for NO_2 (from the dispersion models; the LUR estimated no exceedances), 878 which exceeded the $PM_{2.5}$ guideline (10 µg/m^3) and 64 which exceeded the PM_{10} guideline (20 µg/m^3) (Section 6.3.1.). The air pollution level at these census tracts was brought down to the air quality guideline and the HIA repeated. Compliance with the NO_2 guideline did not reduce the attributable number of asthma cases by even one full case; compliance with the $PM_{2.5}$ guideline reduced the attributable number of asthma cases by 29 cases whilst compliance with the PM_{10} guideline reduced the attributable number of asthma cases by 2 cases.

6.4.4. The Impact of the Baseline Asthma Incidence Rates

Table 39 shows the asthma cases attributable to all pollutants, from all the available exposure models, as estimated using differing baseline asthma incidence rates calculated from Mebrahtu et al. (2015). Compared to the main analyses (Table 37 and Table 38), the number of the estimated attributable asthma cases drops when using the first lower asthma incidence rate (123 per 10,000 person-year) whilst it significantly rises when using the second higher asthma incidence rate (442 per 10,000 person-year), based on treatment (Section 6.3.3.).

As the percentage of air pollution attributable asthma cases from the all-cause asthma cases does not change with changing baseline asthma incidence rates, the relevance of the different estimates shown in Table 39 is demonstrated in monetary values. The aim of this exercise is not to cost the health impacts per se but to simply demonstrate the impact which baseline asthma incidence rates have from a policy perspective. According to Nunes et al. (2017), the annual average cost of an asthma case in

Europe was estimated at $USD 1,900 (£1,264 using 2013 average exchange rate which corresponded to the underlying data). Using the first baseline asthma incidence rate of 123 per 10,000 person-year, the annual cost of asthma attributable to air pollution in Bradford ranged from £315,875 to £779,580. However, using the second baseline incidence rate of 442 per 10,000 person-year, the annual cost of asthma was 3.6 times as much; ranging from £1,135,887 to £2,801,180, depending on the exposure model and the pollutant investigated (Table 39).

Table 39 Estimated Annual Attributable Asthma Cases in Bradford All Available Exposure Models and Differing B*aseline Asthma Incidence Rates*

Model	Pollutant	Attributable cases	Attributable cases lower CI	Attributable cases upper CI	Percentage of all cases	Estimated cost/year
Baseline asthma incidence = 123 per 10,000 person-year Baseline asthma incident cases = 1641						
Snapped COPERT	NO_2	**288**	125	384	**18%**	£363,888
Snapped COPERT	NO_x	**476**	-181	876	**29%**	£601,426
Snapped PHEM	NO_2	**285**	123	379	**17%**	£360,098
Snapped PHEM	NO_x	**470**	-178	868	**29%**	£593,845
LUR	NO_2	**391**	172	515	**24%**	£494,029
LUR	NO_x	**617**	-251	1073	**38%**	**£779,580**
LUR	$PM_{2.5}$	**438**	163	657	**27%**	£553,413
LUR	PM_{10}	**549**	250	778	**33%**	£693,662
LUR	BC	**250**	101	402	**15%**	**£315,875**
Baseline asthma incidence = 442 per 10,000 person-year Baseline asthma incident cases = 5896						
Snapped COPERT	NO_2	**1,036**	448	1381	**18%**	£1,308,986
Snapped COPERT	NO_x	**1,709**	-649	3150	**29%**	£2,159,322
Snapped PHEM	NO_2	**1,022**	441	1363	**17%**	£1,291,297
Snapped PHEM	NO_x	**1,687**	-639	3118	**29%**	£2,131,525
LUR	NO_2	**1,403**	617	1850	**24%**	£1,772,691
LUR	NO_x	**2,217**	-902	3857	**38%**	**£2,801,180**
LUR	$PM_{2.5}$	**1,574**	586	2363	**27%**	£1,988,749

LUR	PM_{10}	**1,974**	900	2794	**33%**	£2,494,149
LUR	BC	**899**	364	1443	**15%**	**£1,135,887**

6.4.5. The Impact of adding Minor Road and Cold Start Concentrations to the Background NO_x Levels

As adding minor road and cold start concentrations to the snapped COPERT-based model estimates improved the performance of the model (Table 32), the HIA calculations were repeated using the snapped COPERT-based model estimates + minor roads and cold starts concentrations, and the new results were compred to the main analysis (Table 37). Table 40 shows that the addition of minor road and cold start concentrations almost doubled the asthma cases attributable to traffic, bringing the percentage of the air pollution attributable asthma cases from 3% up to 7% for traffic-NO_2 and from 6% up to 12% for traffic-NO_x. Interestingly, the inclusion of minor roads and cold starts also brought the estimates of the two exposure models, the dispersion and LUR models, closer (Table 38 and Table 40).

Table 40 Estimated Annual Attributable Asthma Cases in Bradford using the Snapped COPERT Dispersion Models complemented by minor road and cold start concentrations (*baseline asthma incidence = 137 per 10,000 person-year, baseline asthma incident cases = 1827*)

Model	Pollutant	Attributable cases	Attributable cases lower CI	Attributable cases upper CI	Percentage of all cases	Attributable cases to traffic
Snapped COPERT + minor roads and cold starts	NO_2	**394**	173	520	**22%**	**128 (7%)**
Snapped COPERT + minor roads and cold starts	NO_x	**638**	-256	1125	**35%**	**219 (12%)**

6.5. Discussion

6.5.1. Summary

In summary, this work used two full-chain exposure assessment models, to estimate the exposure to NO_x and NO_2 at the census tract level and estimate the childhood asthma cases attributable to these exposures. The contribution of TRAP to the exposures was specifically quantified, once excluding minor road and cold start concentrations and once including them. To compare the attributable childhood asthma cases estimated using the full-chain exposure assessment models to those attributable using commonly used exposure assessment models, the census tracts NO_2 and NO_x exposures were also derived using the Bradford's ESCAPE LUR models (Beelen et al., 2013). Moreover, the ESCAPE's LUR models provided exposure estimates for other pollutants: PM_{10}, $PM_{2.5}$ and BC and these were also used in the analysis. In sensitivity analyses, different (higher and lower) baseline asthma incidence rates were used.

Depending on which pollutant is considered to be the putative agent, the results indicated that 15%-38% of new childhood asthma cases in Bradford are attributable to the exposure to air pollution. The health impacts estimated were sensitive to the exposure assessment model used, the pollutant selected in the analysis but, differently from the initial hypothesis, not the vehicle emission factors used in the full-chain models. Using the full-chain models, the contribution of TRAP to the air pollution attributable asthma burden was specifically quantified and was smaller than expected; ranging between 3%-6%. When minor road and cold start concentrations were included, this contribution almost doubled bringing the burden of disease from 3% to 7% for traffic-NO_2 and from 6% to 12% for traffic-NO_x. This contribution, however, is still likely to be higher in reality as all models tended to under estimate TRAP. Within the LUR models' analyses, the pollutant selection resulted in different attributable asthma burden ranging from 15% (for BC) to 38% (for NO_x). A very small number of census tracts was estimated to exceed air quality guidelines for applicable pollutants. As such, compliance with air quality guidelines did not result in large reductions in the attributable asthma burden. However, these findings may also relate to the models' overall air pollution under estimation. The use of the different baseline asthma incidence rates resulted in large differences in the estimated attributable number of cases which would translate into highly variable monetary burdens and are particularly relevant in the context of asthma.

6.5.2. Strengths

This study is one of the very few studies undertaking full-chain burden of disease assessment that considers the full-chain from exposure source, through pathways to health outcomes (Nieuwenhuijsen et al., 2017) and is the first study to apply this assessment in the context of childhood asthma (Table 33). Further and to the best of the author's knowledge, there have not been any previous attempts to estimate the air quality and associated health impacts using dispersion models with different vehicle emission factors (Chapter 5). This work has therefore contributed to filling this knowledge gap and advancing our understanding of the vehicle emission factors' effect on dispersion modelling results and associated health impacts. This effect was minimal as the differing vehicle emission factors (COPERT or PHEM-based) did not make a difference to the validation parameters (see Sections 5.4.4. and 5.4.5.) or to the health impacts subsequently estimated (Table 37). This is a new finding and can be viewed as either 1) supporting the use of standard vehicle emission models such as COPERT or perhaps more reasonably as 2) pointing to the need for and potential of further work to improve accuracy of the full-chain modelling right at the first stages of traffic modelling (e.g. see Section 5.5.2. and 5.5.3.).

This work adds to the literature by exploring the differences between the estimated health impacts associated with dispersion models' and LUR models' NO_2 and NO_x exposure estimates. The attributable burden resulting from the use of these models differed by 6% to 9%, which, considering the fundamental differences between the models (Khreis and Nieuwenhuijsen, 2017), was considered as good agreement. The agreement between the LUR and the full-chain exposure model estimates' may be further improved by addressing the overall NO_x under estimation in the dispersion models. Indeed, when minor road and cold start concentrations were included in the dispersion models, the attributable burden resulting from the use of the LUR versus the dispersion model differed by only 2% and 3%. This relatively good agreement between health impacts estimated using LUR and dispersion models is in line with scarce literature which shows similar HIA estimates using LUR and dispersion models exposures (Rojas-Rueda et al., 2012).

Another strength of the current study is the generation and use of meta-analytical exposure-response functions to estimate the attributable asthma cases (Khreis et al., 2017d). Meta-analytical exposure-response functions are recommended in HIA (Nieuwenhuijsen et al., 2017), are more precise than point estimates (Perez et al., 2009) and are considered more generalizable and arguably preferable in this study as no local exposure-response functions for Bradford's population were available. Further, the use of the meta-analytical exposure-response functions derived in this study allowed exploring specific impacts of 5 different pollutants (Khreis et al., 2017d), something which was restricted by the lack of pollutant-specific exposure-response functions in the past (Table 33). It, however, is important that the different pollutants' impacts are not added but are treated as independent estimates of exposures that are highly correlated (Khreis et al., 2017c).

Finally, sensitivity analyses were conducted to demonstrate the impact that different baseline asthma incidence rates have on the burden of disease assessed. The relevance of this to policy decision making was demonstrated in monetary terms. This issue has not been explored in previous literature (Table 33). As shown here, the impacts of baseline asthma incidence rates were considerable and are particularly relevant as underlying asthma incidence rates are uncertain, due to the complexity of asthma, the difficulties in its diagnosis and assessment (see Section 1.2.), and the poor consensus on the definition of the condition (Khreis et al., 2017d, van Schayck and Boudewijns, 2017).

6.5.3. Limitations

Despite its strengths, the approach also has its limitations. The key limitation of this work is that TRAP was likely to have been under estimated and therefore the contribution of TRAP to the attributable asthma cases is likely under estimated as well (see Figure 68 and associated discussion). On average and when compared to the ESCAPE measurements, NO_x estimates from the full-chain exposure models were under estimated by 15 $\mu g/m^3$ (see Section 5.4.5.). This under estimation is thought to be in large part due to under estimation in TRAP which on average accounted for 2.5 $\mu g/m^3$ or 13% of all estimated ambient NO_x (Table 25). In fact, the literature documents that traffic contributes to 48% (Nieuwenhuijsen and Khreis, 2016) and 67% (Beevers et al., 2013) NO_x in urban areas, a percentage that is well above the 13% estimated by this study's models. Further, when adding minor road and cold start concentrations to the dispersion models, this under estimation persisted, but to a lesser extent. There was also evidence that the LUR models under estimated NO_x and NO_2.

The background NO_x maps were also poorly resolved and may be an under estimation of NO_x in some areas. The sites where NO_x was under estimated were 14 (out of 15) traffic sites, 20 (out of 24) urban background sites and one (out of 2) regional background site (Table 29). At the 14 traffic sites, NO_x was under estimated by 34%, on average; at the 20 urban background sites, NO_x was under estimated by 24%, on average whilst at the regional background site NO_x was under estimated by 10%, on average (Table 29).

To further illustrate these points and their potential influence on the asthma attributable cases estimated in this study, the reader is referred to scenarios presented in Table 41, which will be now discussed in turn. ***Row 1*** in Table 41 shows that based on the average NO_x levels recorded at urban background and traffic sites in the ESCAPE campaign (originally from Table 23), traffic is estimated to contribute to 35% (or 21 $\mu g/m^3$) NO_x, extra to the urban background NO_x levels. Based on this percentage contribution, and assuming a linear relation between the percentage of traffic NO_x and the asthma cases attributable to traffic NO_x [4], then 240 (i.e. 35% * 687) out of the 687 asthma cases attributable to all NO_x, are due to traffic NO_x. This would represent 13% of asthma cases attributable to all causes (***Row 1***, orange cell). However, and as realized from ***Row 3*** where the traffic-related NO_x and associated asthma cases were quantified explicitly using the COPERT-based dispersion model, the relation between the percentage of traffic NO_x and the asthma cases attributable to traffic NO_x is not simply linear (otherwise 69 (***Row 3***, orange cell) instead of 109 (***Row 3***, green cell) asthma cases should be attributable to traffic NO_x). Instead, in the case of the dispersion model, the relation is not linear but is governed by a scaling factor of 1.59 (69/109 (***Row 3***, orange cell) / (***Row 3***, green cell)), which may represent the unequal distribution of population-weighted traffic NO_x exposures. Using this scaling factor and assuming that the LUR's traffic NO_x is distributed similarly to the dispersion model's traffic NO_x, asthma cases attributable to traffic NO_x using the LUR model are estimated at 21% or 383 childhood cases (***Row 1***, green cell).

Another plausible scenario is presented. As the ESCAPE design allowed urban background sites to be within 50 m of roads with < 3000 vehicles/day (Table 23), the ESCAPE average NO_x at the urban background sites was assumed to include some traffic-related component and therefore its use may under estimate the traffic percentage contribution calculated in ***Row 1***. In ***Row 2*** and based on the DEFRA background's map average NO_x and the average NO_x at the ESCAPE's traffic and background sites together, it is estimated that traffic contributes to 63% (or 29.4

[4] Meaning that if X $\mu g/m^3$ NO_x is responsible for Y childhood asthma cases, then 0.35 X $\mu g/m^3$ NO_x is responsible for 0.35 Y childhood asthma cases, and so on.

μg/m^3) NO_x, extra to the urban background NO_x levels. Again, assuming a linear relation between the percentage of traffic NO_x and the asthma cases attributable to traffic NO_x, 433 (24%) out of the 687 asthma cases attributable to overall NO_x, are due to traffic NO_x (***Row 2***, orange cell). This goes up to 38% if the scaling factor of 1.59, as discussed above, is used. However, 38% is equivalent to 689 cases, which is higher than the total NO_x attributable cases (687) and therefore this suggest that the 1.59 scaling factor is likely unrealistic and overestimating the number of children exposed to traffic NO_x from the LUR. This may indicate that the spatial distribution of the LUR's traffic NO_x is different than that of the dispersion model's traffic NO_x, which is plausible (Figure 66).

This is a simplistic and hypothetical exercise; the aim of which is to demonstrate 1) why the author believes that a big part of the full-chain exposure models' NO_x under estimation is due to TRAP under estimation and 2) the relevance of the traffic NO_x component for the traffic NO_x attributable asthma cases. Therefore, the percentages of traffic-related NO_x attributable asthma cases presented in ***Rows 1 and 2*** are likely to be more realistic than those estimated from the full-chain exposure models and presented in ***Row 3*** e.g. the 6% attributable asthma cases estimated using the COPERT-based dispersion model. The same arguments are applicable when using the PHEM-based dispersion model and when investigating NO_2, instead.

Other limitations are considered less influential. Another limitation relates to the use of exposure estimates averaged at the census tract level. Similarly to other HIA studies, this work draws on exposure proxies (outdoor census tracts average exposure) that cannot fully capture actual exposure variability in the population (Mueller, 2017). Exposure variability may be due to 1) the population mobility as it is unknown whether the population studied spend most of their time in their residential census tracts, indoors or outdoors or due to 2) the high variability in air pollution levels within the same census tracts themselves. This may lead to exposure misclassification (Nieuwenhuijsen, 2015, Ashmore and Dimitroulopoulou, 2009) and potentially distort the health impacts estimated.

Further, NO_2 was generated by conversion of the NO_x levels estimated from the dispersion models (see Section 5.5.3). This is a simplistic procedure that conceals spatial variability of NO_2 levels due to the spatial variability of primary NO_2 sources and therefore may result in exposure misclassification. Further, this study used modelled, rather than measured, air pollution data; being the only feasible way to assign exposure at the scale of Bradford's childhood population. This is considered as a limitation, yet validation of the modelled data was considered satisfactory.

There are further uncertainties related to the underlying asthma incidence rates, which were scaled down from national estimates (Punekar and Sheikh, 2009) and may differ than the rates of the population under study. Partly for this reason, two sensitivity analyses, using different and Bradford-specific underlying asthma incidence rates, were conducted and a possible range of impacts was documented (Table 39). Further, the attribution of a uniform incidence rate to children across Bradford is a limitation and a spatially variable baseline rate would have been preferable but is not available (Lomas et al., 2016). The uniform incidence rate simplifies a particularly ethnic population in Bradford, where > 50% are South Asian (Wright et al., 2013) and those may have (slightly) varying asthma incidence rates (Mebrahtu et al., 2016, Netuveli et al., 2005), but also possibly varying exposure-response functions e.g. due to differing genetic predispositions (Kerkhof et al., 2010, Gilliland, 2009, Castro-Giner et al., 2009), diet (Gilliland, 2009, Khreis et al., 2017e), stress (Shankardass et al., 2009), violence (Clougherty et al., 2007), social disadvantage or other factors. Sex was also not considered due to the absence of 1) sex-specific incidence rates and 2) sex-specific exposure-response functions, even though sex was shown to have an impact on both asthma incidence rates in the Bradford's childhood population (Mebrahtu et al., 2016) and the exposure-response functions in other studies (Khreis et al., 2017d, Clougherty, 2010). All the above factors were not considered due to the unavailability of more specific exposure-response functions and asthma incidence rates that may better reflect true variability in the parameters and/or susceptibility of the underlying childhood population.

6.5.4. Conclusions

This study provides the first full-chain HIA of TRAP and childhood asthma; using pollutant-specific meta-analytic exposure-response functions (Khreis et al., 2017d) and considering the full-chain from exposure source, through pathways to health outcomes. The burden of childhood asthma attributable to air pollution is poorly documented and this study adds to the scarce literature estimating that 15% to 38% of all childhood asthma cases in Bradford are attributable to air pollution. The choice of the pollutant and the exposure model made a difference to quantified impacts, but the choice of the vehicle emission factors did not. The results presented here are likely to be an under estimation of the impact of air pollution, particularly that due to traffic (TRAP). TRAP might have been significantly under estimated, mainly due to the combination of low vehicle emission factors and overestimated speeds.

Table 41 Average Urban Background and Average Traffic NO_x Concentrations (µg/m^3) from the Different Datasets/Models and TRAP Attributable Asthma Cases

Row number ----------------------------- Scenario description	Urban background dataset ----------------------------- Traffic dataset	Average NO_x at urban background sites (µg/m^3)	Average NO_x at traffic sites (µg/m^3)	Average traffic contribution (µg/m^3) (=Traffic NO_x - Urban background NO_x)	Average percentage of traffic contribution (Traffic contribution/ Traffic NO_x)	Overall NO_x attributable asthma cases ----------------------------- Assumed traffic-related NO_x attributable asthma cases, based on linear relations (% traffic contribution * overall attributable cases)	Scaled traffic-related NO_x attributable asthma cases
Row 1 ----------------------------- Using only ESCAPE measurements	ESCAPE measurements ----------------------------- ESCAPE measurements	38.4	59.4	21	35%	687 (38%) using LUR (Table 38) ----------------------------- 240 (13%) (= 35% * 687)	383 (21%) (=240*1.59)
Row 2 ----------------------------- Using ESCAPE measurements at traffic and urban background sites and DEFRA background map	DEFRA map ----------------------------- ESCAPE measurements	17	46.4	29.4	63%	687 (38%) using LUR (Table 38) ----------------------------- 433 (24%) (= 63% * 687)	689 (38%) (=433*1.59)
Row 3 ----------------------------- Using COPERT-based dispersion modelling including DEFRA background map	DEFRA map ----------------------------- COPERT-based dispersion model (snapped)	17	19.5	2.5	13%	530 (29%) using COPERT-based dispersion model (Table 37) ----------------------------- 69 (4%) (= 13% * 530)	109 (6%) (=69*1.59)

7 Discussion, Future Work and Conclusions

7.1. Summary and Conclusions

The present thesis presents the estimation of the impact of TRAP exposures on the development of new cases of childhood asthma. This was done using quantitative methods to assess the risk (by producing meta-analytic risk estimates) and the burden (by producing burden of disease estimates) of childhood asthma associated with and attributed to TRAP exposures. In the first chapter, several issues in past research were outlined. Of importance were 1) the inconsistent and outdated evidence base linking TRAP and the development of childhood asthma, 2) the poor documentation of the impact of exposure to TRAP on the burden of childhood asthma, 3) the lack of full-chain HIA models tracking the exposure source, through pathways to health outcomes and 4) the uncertain and unreliable vehicle emission factors. These issues highlighted a need for a new synthesis of a rapidly growing evidence base concerned with TRAP and childhood asthma, and the development of improved full-chain HIA models which provide more realistic estimates of vehicle emissions and quantify the burden of asthma due to TRAP exposures. The work reported in this thesis addressed these issues and added to the literature as follows:

- Chapter 2 explored the associations between early-life exposure to TRAP and the subsequent development of asthma in children. It undertook a comprehensive and up-to-date meta-analysis and produced pollutant-specific exposure-response functions (Chapter 2). The novelty of this work was in the synthesis of the evidence base concerned with TRAP as a risk factor of asthma development and the generation of new exposure-response functions for 5 traffic-related air pollutants. The only comparable study focused on TRAP as a risk factor for childhood asthma onset can be found in the HEI Special Report 17: '*Traffic-Related Air Pollution: A Critical Review of the Literature on Emissions, Exposure, and Health Effects*', yet, at that time, a meta-analysis was not possible (Health Effects Institute, 2010).
- In Chapter 4, a new set of average-speed-emission functions (i.e. a new emission model) was developed and compared to the standard average-speed-emission functions sourced from the widely used European model:

COPERT. The new emission model was underlined by real-world and local driving cycles, PHEM-based instantaneous NO_x emission estimates and a novel micro-trip averaging approach which split the driving cycles and associated emissions into driving events between consecutive stationary periods. There were no comparable studies in the literature and this study proposed a new practical approach for the derivation of new average-speed-emission functions, which can be adopted in the future in full, or partially, and can be very valuable for the the assessment of local traffic and transport policies.

- Following work linked traffic, emissions and atmospheric dispersion models and developed two novel full-chain exposure models of TRAP (Chapter 3, 4 and 5), each populated with a different set of average-speed-emission functions: the standard and the newly developed one (Chapter 4). Air pollution levels estimated from the full-chain exposure models were validated against 4 available data sets and compared to a third LUR model; an exposure model commonly used in air pollution epidemiological and HIA studies (Chapter 5). The novelty of this work was in the development of the full-chain exposure models, their validation against multiple data sets and exploring the differences in the air pollution estimates based on the exposure model (LUR or full-chain) and the emission model (COPERT or PHEM-based) used. The literature pertaining to these points was shown as either scarce or absent.
- Chapter 6 linked the full-chain exposure estimates with baseline health data and the newly generated exposure-response functions to produce a full-chain HIA model which estimated the impact of exposure to air pollution, and particularly TRAP, on the burden of childhood asthma in Bradford (Chapter 6). The novelty of this final work was in its cross-disciplinarity, combining all previous elements developed in this thesis in one newly developed full-chain HIA model which quantified the asthma BoD related to air pollution, and to TRAP, specifically. This study provided the first full-chain HIA of air pollution and childhood asthma with specific estimates for the contribution of traffic.

Beyond these specific contributions, this work presents a complete interdisciplinary piece of research, mapping the whole spectrum from vehicle emissions to their health impacts, in a multi-ethnic deprived city suffering from childhood asthma rates higher than national and regional averages.

An important strength of this interdisciplinary inquiry was to demonstrate the process of developing the full-chain HIA models whilst highlighting the potential uncertainties of full-chain quantitative HIA and presenting an outlook into how modelling of this sort may be improved and better utilized.

7.2. Discussion

Going back to the specific research objectives laid out at the outset of this study (Box 1, Section 1.3.), this research achieved its objectives and arrived at the following conclusions.

7.2.1. Research Objectives

- **<u>Question 1 – Can early-life exposure to TRAP drive the subsequent development of asthma in children (from birth to 18 years of age)?</u>**

The first study in this thesis provided sufficient evidence to support an association between the exposure to TRAP and the development of childhood asthma, from birth to 18 years of age. The study was a systematic review and a meta-analysis to analyse the association between TRAP and asthma development in childhood, with a focus on early-life exposures (Khreis et al., 2017d). The study was followed up with a qualitative analysis which reviewed and appraised the exposure assessment methods, highlighted recent advances, remaining research gaps and made suggestions for further research (Khreis and Nieuwenhuijsen, 2017). The study filled a gap in the existing literature by qualitatively and quantitavely synthesizing and appraising a rapidly developing evidence base specifically focused on TRAP exposure as a risk factor for childhood asthma. The findings demonstrated that there was a recent rapid growth in the number of eligible articles with 44% published after 2014 and that there was significant heterogeneity across the studies in terms of outcome definitions, exposure assessments, pollutants studied and statistical methods, but some move towards harmonization (e.g. ESCAPE and MeDALL projects). The findings also showed that there were no studies which explicitly attempted to distinguish the effects of TRAP from the effects of other air pollution sources e.g. using full-chain exposure assessment models or equivalent methods. There was some suggestion that the associations might differ based on age, sex and asthma phenotype. However, there was no systematic evaluation in these subgroups, despite previous calls, and these issues still need further assessment and ascertainment (Health Effects Institute, 2010, McConnell et al., 2006). The strengths of this study were fully discussed in the corresponding chapter and mainly included its large and up-to-date coverage, its novel focus, its in-depth meta-analyses and its generation of new pollutant and age-specific exposure-response functions for a range of pollutants wider than previously reported (Anderson et al., 2013, Bowatte et al., 2015, Gasana et al., 2012, Favarato et al., 2014). These exposure-response functions are currently being used in a European-wide and a US-wide HIA conducted by the author. The limitations of this study were also discussed and mainly included its underlying assumption that early-life represents the most critical exposure window for the development of asthma, the low number of studies included in some of the meta-analyses (e.g. BC and NO_x), the lack of equivalence among some of the exposure measures, populations studied and 'asthma' definitions and the assumption that the relationship between the exposure and the outcome was log linear. Overall, this study supported the hypothesis that TRAP exposures drive the subsequent development of childhood asthma. It further suggested that future studies could usefully focus on a number of more advanced aspects and questions, beyond trying to demonstrate the association between TRAP and the onset of childhood asthma. These mainly included using full-chain exposure models to distinguish effects of TRAP from other sources; systematically investigating associations with multiple windows of exposure; expanding the focus on NO_2 to other pollutants and using multiple pollutant models; exploring whether threshold effects exist; expanding the methods of asthma assessment beyond reporting of doctor-diagnosis; assessing the effect of disease misclassification on the exposure-response functions; formally assessing the drivers of heterogeneity and systematically investigating potential susceptible subgroups.

- **Question 2 – Were there pollutant-specific effects and what is the magnitude of the exposure-response functions?**

The first study also showed that there were statistically significant and positive associations between BC, NO_2, $PM_{2.5}$, PM_{10} exposures and risk of asthma development in children but no way to disentangle the effects of one pollutant from another. The association with NO_x was also positive but not statistically significant. The magnitude of the exposure-response functions for the 5 investigated pollutants was estimated and was a key output of the first study which provided previously missing exposure-response functions which can now be readily used in HIA and BoD studies.

There were two key points emerging while exploring the differences in the effects of different pollutants. The first was that the positive and statistically significant associations between TRAP exposures and childhood asthma development were observed for 4 out of the 5 investigated pollutants and that the statistically insignificant association with the fifth pollutant: NO_x were may be due to the lower number of studies available. As such, further research is needed to confirm the magnitude and direction of the NO_x risk estimate; bearing in mind that it could be acting as a surrogate of exposure to ultra-fine particles as levels of these two pollutants near roadways are highly correlated (Kwasny et al., 2010, Yahaya et al., 2012, Health Effects Institute, 2013). Further, while the studies included in the systematic review controlled for key potential confounders, an important limitation was the lack of data on co-pollutants which made a distinction of pollutant-specific effects not possible. These findings are somewhat comparable to the literature. The latest relevant meta-analysis also documented positive and statistically significant associations for 2 (BC, $PM_{2.5}$) out of 3 (BC, $PM_{2.5}$, NO_2) investigated pollutants (Bowatte et al., 2015), whilst a previous one documented a positive and statistically significant association between NO_x and NO_2 exposures and prevalence of asthma symptoms (Favarato et al., 2014). Therefore, the results of the first study, in the context of current knowledge, precluded interpreting the observed effects as a certain pollutant's effect. This is thought to be due to the high correlations amongst these pollutants in traffic exhaust and ambient air (Beckerman et al., 2008, Sarnat and Holguin, 2007).

The second point emerging here was that the heterogeneity detected in the different pollutants' meta-analyses varied significantly, ranging between no estimated heterogeneity for BC (0%), minimal for PM_{10} (29%) and $PM_{2.5}$ (28%) and high for NO_2 (65%) and NO_x (87%). Although interpretation should be cautious due to underlying limitations (e.g. the smaller number of studies available for pollutants other than NO_2; see Table 3), these statistics indicate that NO_2, although commonly studied, may not be the putative agent in the TRAP mixture, but instead act as a surrogate for traffic-related BC, $PM_{2.5}$ or other unmeasured traffic-related pollutants. This question remains open and warrants more attention in future studies.

In line with this recommendation, a recent HEI expert workshop on traffic and health concluded that the question of whether NO_2 is a causal agent (for numerous health outcomes) or an indicator of TRAP was important, but still largely unresolved (Health Effects Institute, 2016). Linked to this point is also the lack of data on the effects of non-exhaust pollutants dominated by tire wear, brake wear, road surface wear, engine wear and re-suspended crustal and street dust particles. With the expected wide-spread introduction of electric vehicles, especially in cities, and the continuing efforts of emission reductions from combustion engines, the relative importance of non-regulated, non-exhaust emissions is large but largely unknown (Khreis and Nieuwenhuijsen, 2017, Timmers and Achten, 2016).

- **Question 3 – Has a new more reliable vehicle emissions model been developed and how does it compare to the standard vehicle emission model?**

In the second study, a new vehicle emission model (PHEM-based) was developed and compared to the standard COPERT vehicle emission model (Khreis et al., 2017b). The new emission model did not make a difference to subsequent air pollution and health impact estimates, nor did it make a difference to the validation of the full-chain exposure models, differently from the initial hypothesis. As such, there was no solid evidence of improvements due to the use of the new vehicle emission model.

However, the new model is likely to exhibit some ‘theoretical’ improvements, as compared to the standard COPERT model. These theoretical improvements were related to the more realistic varying and higher NO_x emission estimates at the lower average-speeds in the average-speed-emission functions (mainly observed at < 20 km/h but varied depending on the vehicle type, for example, see Figure 51). The standard average-speed-emission functions as widely used in the COPERT model were repeatedly shown to under estimate vehicle emissions, especially at low average speed segments characterized by shorter road sections, higher speed (and acceleration) fluctuations and more frequent stop-start driving (Health Effects Institute, 2010, Khreis, 2016, Tate, 2015a) (Section 4.1.4.). These conditions are very relevant and common in urban road networks. For example, in the Bradford SATURN network, 38% of all road links in were ≤ 100 m (Chapter 3). The real-world driving cycles undertaken were driven at speeds ≤ 10 km/h 41% of the time. The standard vehicle emission model under estimation, in part, has to do with the theoretical underpinnings of the COPERT model importantly including 1) its underlying driving cycles which are not realistically transient and only cover limited engine speed and power ranges (Kousoulidou et al., 2010, Khreis, 2016), 2) the inadequate definition of the ‘trip’ interval at which vehicle speeds and emissions are averaged and paired and 3) the mixing of results from thousands of *laboratory* empirical emission tests, right across Europe, yielding average-speed-emission functions with low predictive power (Section 4.1.3.). The new vehicle emission model, was underpinned by real-world observed driving cycles, directly sourced from the study area, and model (PHEM)-

based instantaneous emission estimates which were averaged over ‘micro-trip’ intervals. At speeds < 10 km/h, the new PHEM-based model resulted in significantly higher emission estimates than the COPERT model; which for some vehicle types were up to 4 times higher (Figure 59).

In the context of the current knowledge, these estimates are considered more realistic and theoretically more correct. However, the newly developed vehicle emission model generally estimated less emissions at the higher speed ends, something which is not necessarily accurate (Hausberger, 2002, O'Driscoll et al., 2016), but may be explained by the lack of data points at those ends. There were two key points which emerged from this work and that warrant further reiteration.

The first was that the new vehicle emission model, although theoretically more realistic where COPERT’s reliability was limited (i.e. at low average speeds), did not make a worthwhile impact on improving the dispersion model’s accuracy and still resulted in overall air pollution under estimations. These under estimations were very similar in magnitude to the under estimation documented when using the COPERT-based dispersion mode. This result was rather unexpected at first, but further exploration revealed that the lack of low speed traffic from the traffic model probably had to do with this under estimation. This insight pinpointed a previously unrecognized point at the outset of this study: improvements in the emission modelling will not result in overall improvements in air pollution estimates. These are only likely when improvements in emission modelling are coupled with improvements in traffic modelling; to better capture the temporal variation and the lower average speeds across the urban road network. In particular, the overall underestimation of vehicle emissions may be traced back to the lack of low average speed segments in the SATURN traffic network. Whether more realistic, slower, average speed links will result in better estimates of vehicle emissions and associated TRAP is a matter that is unknown and that warrants further analysis. Further, the author also believes that both the PHEM and COPERT emission models under estimate real-world driving emissions, due to disregarding temperature and gradient effects (Dardiotis et al., 2012, Frey et al., 2008, Sayegh et al., 2016, Weilenmann et al., 2009, Westcott, 2016), and not accounting for the underperformance of NO_x emission controls in real-world urban driving (Tate and Connors, 2014, Carslaw et al., 2011a), amongst others.

The theoretical improvements in the new emission model, however, may be utilized in other applications and investigations that were outside the scope of this study. For example, and of particular policy relevance, traffic calming measures, mainly designed and implemented to improve safety of road users, might increase start-stop driving and therefore vehicle emissions. The average-speed-emission functions developed in this work can aid in estimating the impact of such measure on local exhaust emissions and associated TRAP.

The second point emerging from this work was the notably different source apportionment resulting from using the two emission models. When using the PHEM-based model, the focus was shifted from passenger cars to HDVs, buses and coaches. This trend is in line with the very scarce literature and shows how sensitive source apportionment is to the underlying emission modelling approach (Peace et al., 2004). The strengths of this study were fully discussed in the corresponding chapter and mainly included the development of new average-speed-emission functions underlined by real-world and local driving cycles, the use of the micro-trip as the unit over which instantaneous vehicle speeds and emissions were averaged and paired and the relative practicality, transparency and transferability of the emission model development approach, either in full or in parts. The limitations of this study were also discussed and mainly included the lack of vehicle emission measurements and the over-reliance on modelling approaches, the incomplete validation of the PHEM and COPERT emission models, the lack of data at the higher speed ends and not taking vehicles' age and maintenance parameters into account. Overall, in the second study, a new vehicle emission model was developed and compared to the standard COPERT model. However, and despite the assumed improvements in emissions estimation at the lower average speed segments, the new model did not make a difference to the overall accuracy of the air quality estimates nor to the magnitude of subsequent BoD estimates. The over-reliance on emission modelling, rather than the combination of emission measurements and modelling, and the lack of comprehensive emission data which could be used for the calibration and validation of models, are key and persistent challenges that future research and practice are yet to address.

- **<u>Question 4 – Has a full-chain exposure assessment model linking traffic, emissions and atmospheric dispersion models been developed?</u>**

In the third study, two full-chain exposure models of TRAP, each populated with a different set of average-speed-emission functions, were developed by running and linking the following independent models: SATURN (traffic model), COPERT and PHEM (emission models) and ADMS-Urban (atmospheric dispersion model) (Khreis et al., 2018, Khreis et al., 2017c). The linkage of these models is what the author refers to as the full-chain exposure assessment model. Full-chain exposure assessment models are missing in HIA studies of TRAP and asthma (Table 33) whilst they are very few in epidemiological studies of TRAP and asthma (Table 1). This study, therefore, fills this gap and articulates a methodology for the linkage and verification of the chain's models. The key advantages of the full-chain exposure model are twofold. First, the models enable the explicit quantification of the contribution of traffic to levels of ambient air pollution and subsequently to the asthma BoD associated with these levels. From a policy perspective, this is valuable as it enables specific and explicit quantification of the health impacts of TRAP (Nieuwenhuijsen et al., 2017), and can provide valuable feedback for improving regulatory or other action (Samet, 2003). From a scientific perspective, this was also valuable as this full-chain assessment approach provided further insight into the dispersion models under estimation and the potential reasons behind this, mainly including the low vehicle emission factors and the under estimation of congestion within the traffic network. The second advantage of the full-chain exposure modelling is perhaps more relevant for applied science and tools and models' development. The modelling of the holistic chain of traffic, emissions and air pollution, by one individual (the author), clearly highlighted the uncertainties, data, expertise, technology and model feature gaps in current knowledge and practice. These were outlined in their relevant chapters but are also synthesized in one place in the next section. Overall, the development of the full-chain exposure assessment models was laborious and highly time-consuming. The better provision and documentation of input and validation data, technological and model features improvements (see Figure 69) including a higher flexibility in dispersion model inputs and the development of programs which can automatically integrate the different models (Namdeo et al., 2002), would greatly help the process and facilitate its wider adaptation. Further and because the datasets underlying this research study were burdensome to collate and/or generate but can be utilized in other applications, these are being made open access alongside their meta-data, to maximize their utility for the research, practice and policy-making communities.

- **Question 5 – What is the burden of childhood asthma attributable to TRAP?**

In the fourth study, the burden of childhood asthma attributable to air pollution in general, and to TRAP in particular, was estimated (Khreis et al., 2018, Khreis et al., 2017c). In Bradford, the annual childhood asthma cases attributable to air pollution ranged from 279 (113, 447) to 687 (-279, 1196) cases or from 15% to 38% of all asthma cases, depending on the pollutant studied and the exposure assessment method used. Using the full-chain exposure assessment models, the childhood asthma cases attributable to the traffic component of air pollution was possible to estimate and equalled 3% for NO_2 and 5% to 6% for NO_x, depending on the vehicle emission modelling method used. However, and as discussed in more depth in the relevant section, there was reason to believe that these figures are significantly under estimated as the dispersion models under estimated NO_x by 15 µg/m^3 or 32%, on average. This under estimation is well documented in the literature and is likely to be, in big part, due to under estimation in the traffic-related component of air pollution, which only accounted for 13% of the overall average NO_x, a ratio that is well below the ratios often cited in the literature (e.g. 48% to 67%) (Nieuwenhuijsen and Khreis, 2016, Beevers et al., 2013). Indeed, when minor road and cold start concentrations were included, this contribution almost doubled bringing the burden of disease from 3% to 7% for traffic-NO_2 and from 5-6% to 12% for traffic-$NO_{x.}$ This contribution, however, is still likely to be higher as all models tended to under estimate TRAP

If the traffic-related component was *not* under estimated, the attributable asthma cases could have accounted to a significantly larger percentage of asthma cases which the author tried to quantify indirectly e.g. 24% (Table 41). Overall, these findings suggest that full-chain exposure assessment models, despite their key advantage of tracing the health impacts back to the exact sources of the risk factor, can significantly underestimate TRAP exposures and the associated BoD. Again, and linked to Question 3 above, there is a clear need to improve the full-chain exposure modelling approach, most notably by improving the traffic speeds data, which were overestimated, and the vehicle emissions data, which were under estimated.

- **Question 6 – Do the different exposure assessment methods and different vehicle emissions assessment methodologies translate into different estimated disease burdens?**

Also, in the fourth study, health impact estimates from the full-chain exposure models were compared to estimates from LUR models developed for Bradford as part of the ESCAPE project. As discussed above, changes in the vehicle emission assessment methodologies did not make a noticeable difference to the BoD estimated. However, the choice of the exposure assessment model did, as the LUR models estimated a higher BoD than the full-chain exposure models, by up to 9%. This difference was reduced significantly, however, when minor road and cold start concentartions were included in the models. Then, the attributable burden resulting from the use of the LUR versus the dispersion model differed by only 2% and 3%.

LUR models have recently become the chosen exposure assessment method to capture small-scale differences in air pollution levels, particularly those originating from traffic sources (de Nazelle et al., 2013). Numerous epidemiological and HIA studies use LUR models to investigate health effects and impacts of exposures to air pollution (Khreis and Nieuwenhuijsen, 2017, Hoek et al., 2008, Jerrett et al., 2005, Mueller, 2017). This study's findings showed that the correlations between air pollution estimates from the full-chain versus the LUR models were moderate (R^2 between 22% and 34%), and that the LUR model, on average, predicted higher NO_x (by up to 30%) and NO_2 (by up to 55%). In terms of the estimated BoD, the use of the LUR model therefore resulted in higher estimated asthma attributable cases showing that the exposure assessment method selected makes a difference to the final results. In the literature, there is only little research on the impacts of the exposure assessments on estimated health effects or impacts (Khreis and Nieuwenhuijsen, 2017, Rojas-Rueda et al., 2012), and this study further adds to this limited evidence base. Within the LUR models themselves, this study also showed that the choice of the pollutant makes an important difference to the BoD estimated with ranges between 15% for BC and 38% for NO_x. These differences had to do with the clearly different exposure-response functions and the different spatial distribution of the 5 pollutants studied. The preferred pollutant to be studied, however, is not so obvious since co-pollutant data was limited, and the distinction of pollutant-specific effects was not possible (Question 2). The preferred method for exposure assessment is also not so obvious and depends on available resources, the quality of the input data, expertise, place of study and transferability considerations. As it stands, the full-chain exposure models still need refinement, especially regarding their traffic and emission inputs and the LUR models perhaps offer a more realistic and higher air pollution and BoD estimates, at a lower implementation cost.

- **<u>Question 7 – What are the remaining knowledge gaps and the uncertainties at each step of the full-chain modelling; what are the alternative options and the research and practice needs to advance the current state-of-art?</u>**

Finally, the following section provides an overall and integrated synthesis of the documented (Table 42) and potential (Table 43) uncertainties of full-chain quantitative

HIA and presents an outlook into how modelling of this sort may be improved in the future. Currently, there is a wall between the different disciplines, and the steps of the full-chain quantitative HIA model developed in this work are distinct and often undertaken by different research and practice communities (Figure 1). This is significant, as there are different (alternative) data sources and decisions to be made along the full-chain, or the parts of it. These selections will have impacts on the final results, their validity and their utility. Therefore, the process of the full-chain modelling presented in this thesis including obtaining, verifying and selecting data and linking together the different models and datasets is considered important as it highlighted the uncertainties in current knowledge and practice and shed light potential for improvements.

7.2.2. Uncertainties and Avenues for Future Work

Table 42 is an overall and integrated synthesis of the *documented* uncertainties or errors at each stage of the full-chain quantitative HIA model. Table 43, on the other hand, is an overall and integrated synthesis of the *potential* uncertainties or errors at each stage of the full-chain quantitative HIA model.

For each uncertainty or error item, a fuller description is provided alongside an indication of the documented/estimated or likely effect(s) including the stage at which the effect occurs, the likely direction of the effect (i.e. under estimation, over estimation, inaccuracy/unknown) and the relative impact of the effect (high, moderate or low), as assessed by the author, based on results from, and professional judgement and experience gained during, this study. The last column is a description and/or proposition of alternative data sources, methods and tools which can improve the practice of this study. A description and discussion of this study's practice and the motivation behind all selections have been presented in the relevant chapters and are not repeated here. A precise quantification of each uncertainty's impact on final estimates is a matter worthy of another research study and can be explored in depth by rerunning the full-chain models with varying inputs.

The key observation the reader can gauge from Table 42 is that the uncertainties or potential errors occurring at the first stages of the modelling including the traffic then the emission modelling stages are more influential and impactful than errors which occur in later stages of the chain. The reason is simply that these errors can propagate through the whole chain and theoretically influence all following items.

The key uncertainties in the **traffic modelling** stage are in the 1) traffic speeds and flows estimations, 2) the exclusion of motorcycles traffic (and emissions), 3) the use of national traffic fleet compositions, 4) the exclusion or agglomeration of numerous minor roads in the traffic model, 5) the definition and inaccurate geocoding of road links and 6) the treatment of diurnal and seasonal effects. The first four items are expected to lead to an under estimation in vehicle emissions, air pollution and exposure levels, and health impacts whilst the last two items will distort the accuracy of following estimates, in a direction that is unknown.

The key uncertainties in the **emissions modelling** stage are in the 1) the use of laboratory-based emission models, 2) not accounting for age and maintenance conditions of the vehicle fleet, 3) the limited (in space and time) driving cycles underlying the PHEM-based model development, 4) the selection of NO_x as the primary pollutant to model and 5) the average vehicle specifications used to parametrize the PHEM model. The first two items are expected to lead to an under estimation in vehicle emissions, air pollution and exposure levels, and health impacts whilst the last three items will distort the accuracy of the following estimates, in a direction that is unknown.

The key uncertainties in the **air pollution dispersion modelling and exposure assignment** stage are in the 1) the use of coarsely resolved background NO_x maps, 2) the reliance on meteorological data from one station with 9% missing records, 3) not accounting for built and natural environment features and their impacts on air pollution and exposures, 4) the assignment of exposures at the census tract level, 5) the resolution of the air pollution estimates and the TRAP maps and 6) the NO_x to NO_2 conversion method. Whether these items result in an under or an over estimation is unclear and warrants further investigation.

The key uncertainties in the **exposure-response functions assessment** stage are in the 1) high heterogeneity in the underlying data, 2) the assumption that the relationship between air pollution and asthma development is log-linear, with no threshold, 3) the possibility of publication, reporting and confirmation bias and 4) the lack of ethnicity, age and sex-specific exposure-response functions and data. Whether these items result in an under or an over estimation is unclear and warrants further investigation.

Finally, the key uncertainties in the **health impacts modelling** stage are in the 1) baseline incidence asthma rates and the outcome definition and 2) other competing risk or protective factors that were not accounted for in the exposure-response functions. These uncertainties will distort the final health impacts modelled in a direction that is more difficult to assess. In the case of the baseline asthma incidence rates, an under estimation is possible as asthma is generally under-diagnosed.

This final qualitative analysis reiterates a point that is persistent throughout this thesis. The utility of the full-chain quantitative HIA models is contingent upon improvements in the chain's stages, particularly in the traffic and emission modelling stages, which are thought to be highly influential due to the magnitude of errors at these stages and their early propagation throughout the model. Future studies can focus on these stages and formally test the impacts of changing traffic activity and emission estimates on the final BoD estimates. Overviewing existing and potential alternatives which can improve future full-chain assessments (last column of Table 42), it is likely that the way forward lies in 1) the provision of more complete, accurate and readily available data sets and 2) the use of existing and the development of new affordable technologies that can facilitate the monitoring of wide-scale traffic activity, emission, air pollution, exposure, and mobility patterns which can be used to calibrate, complement and validate models.

Table 42 Full-Chain Quantitative Health Impacts Modelling *Documented* Uncertainties, Likely or Documented Effects and Alternatives

Legend/ colour code

- Traffic modelling stage
- Emissions modelling stage
- Air pollution dispersion modelling and exposure assignment
- Health impacts modelling stage
- Exposure-response functions assessment stage

Modelling stage	Uncertainty or error	Likely effect			Relative impact			Alternative(s)
		Description	Stage(s) of effect	Likely direction of effect	High	Moderate	Low	
Traffic modelling	Average traffic speed	- Overestimation of average traffic speeds (under estimation of congestion in the SATURN model) - The under estimation of congestion is likely behind a big part of the under estimation in emissions especially when the new PHEM-based model was used, see Section 5.4.3 - Assignment of uniform speed on each road link (disregarding variations over the same road link e.g. due to idling, stop-start driving and different driving patterns) - Assignment of uniform speed for all vehicle classes (disregarding differences in speeds between different vehicle classes on the same road link)	Emissions modelling	Under estimation of emissions	X			Wide-scale direct observations of traffic speeds (and flows) by e.g. videos, GPS tracking (e.g. Tom-Tom or Teletrac), satellite imaging or air photos, repeated monitoring campaigns and remote sensing and/or traffic surveys/diaries. These estimates are likely to be highly resolved in space and time and can give speeds based on vehicle type e.g. average speed for a bus versus another average speed for a car on the same road link. Considering modelling vehicle emissions based on parameters other than average speed e.g. vehicle specific power, acceleration, idling etc.
			Air pollution dispersion modelling and exposure assignment	Under estimation of air pollution and exposure	X			
			Health impacts modelling	Under estimation of health impacts		X		
	Traffic fleet composition	- Vehicle fleet composition proportions given in the NAEI were applied. These were averages over Urban England road networks and not specific to Bradford - Bradford fleet is different than national averages e.g. buses are older and fewer and HDVs are more, see Table 14 - For example, buses and coaches and HDVs proportions, were around 60% higher and 40% lower in the NAEI than in the other fleet composition datasets, respectively - Differential fleet composition may be observed on different road types (e.g. urban versus rural roads versus motorways) and in different time periods	Emissions modelling	Under estimation of emissions		X		The full-chain models could be run again using different vehicle fleet composition figures, directly observed in the study area, and the impact assessed. Different fleet compositions can come from e.g. CBMDC counts or Automatic Number Plate Recognition data, ad-hoc remote sensing campaigns and DfT local traffic counts and classifications (i.e. published and unpublished data). Specific attention should be paid to the collection of information on vehicle emission standards, weight categories etc. or the integration of different datasets. Differential fleet mix for different road types (e.g. urban vs motorways) can be applied but first require the classifications of the roads and then differential fleet compositions. Fleet mix also differs by time of the day but the only possible source of this data is likely observation
			Air pollution dispersion modelling and exposure assignment	Under estimation of air pollution and exposure		X		
			Health impacts modelling	Under estimation of health impacts			X	
	Smaller streets traffic	- Traffic data on minor roads e.g. smallest roads, residential streets, cul-de-sacs, were not included in the SATURN model or these roads were agglomerated into a single link and not represented individually - These streets are likely to contribute to cold-start and idling emissions.	Emissions modelling	Under estimation of emissions	X			The development of future traffic models should be based on underlying road or street maps and attempt to model all/most existing streets in the network. If traffic monitoring is used instead, specific attention must be paid to the inclusion of these smaller streets and their traffic
			Air pollution dispersion modelling and exposure assignment	Under estimation of air pollution and exposure	X			

		Their addition to the full-chain exposure model doubled the TRAP associated burden of disease as compared to the full-chain models without minor roads and cold starts, see Table 37 and Table 40	Health impacts modelling	Under estimation of health impacts	✗			
	Road links definition and geocoding	- SATURN road links were defined as straight lines between nodes and road curvatures were not captured - The geolocations of the nodes and links were inaccurate and therefore the link lengths as well - There were multiple links that were too long where the assignment of one speed and flow over becomes more unrealistic and higher variation is expected - The impacts of attempting to correct the geocoding of the traffic network was minimal in this study and changed the burden of disease estimates by only 2 cases, see Table 37and Table 46 - However, this impact can be more significant and influential if the exposure was assigned at the individual (rather than census population) level	Air pollution dispersion modelling and exposure assignment	Inaccuracy of air pollution and exposure		✗		A better integration between traffic modelling and GIS data is needed. Linked to the above, traffic modelling can be based on underlying road or street maps where road geometry can be accurately identified (e.g. road gradient, curvature, location, etc.). Long links should be cut down to smaller links before modelling traffic and speeds on them. CBMDC are in the process of updating their traffic model accordingly
			Health impacts modelling	Inaccuracy of health impacts			✗	
Emissions modelling	Vehicle exhaust emissions modelling	- Both COPERT and PHEM are emission models primarily built on laboratory emission testing data - This data is unrealistic due to the underlying driving cycles and laboratory conditions e.g. temperature, road gradient, humidity, wind, extra loading, age and maintenance of tested vehicles etc. - Real-world emissions are often higher - Using such emission models in full-chain exposure models can under estimate TRAP levels by up to 74% at the individual validation locations, see Section 5.4.5.	Air pollution dispersion modelling and exposure assignment	Under estimation of air pollution and exposure	✗			Average-speed emission models need fundamental improvement or scrappage. Emission measurements could provide emission estimates instead e.g. using Portable Emission Measurement Systems and remote sensing. These systems, however, will continue to have limited coverage and utility unless cost, practical and privacy challenges are minimized and/or vehicles become regularly equipped with similar monitors e.g. required by policy. Considering vehicle emission modelling based on parameters other than average speed e.g. vehicle specific power, acceleration, idling etc. is also recommended
			Health impacts modelling	Under estimation of health impacts	✗			
	Pollutant selection	- Only NO$_x$ was possible to model with COPERT and PHEM in this study - Estimates of other pollutants especially PM are less reliable and were therefore excluded but would result in different estimated health impacts if included - As shown in this study, the selection of the pollutant in the HIA makes a noticeable dfferent on the burden of disease estimated. For example, BC was associated with 15% of childhood asthma cases in Bardford whilst PM$_{10}$ was associated with over	Health impacts modelling	Inaccuracy of health impacts	✗			Modelling and validating estimates of other pollutants should be attempted in the future

		double that percentage or 33%, see Table 38				
Air pollution dispersion modelling and exposure assignment	Background air pollution maps	- Background NO_x maps from DEFRA may have some inaccuracy - They were also poorly resolved at the 1 km x 1km grid level - Validation of the air pollution estimates showed that at urban background locations, air pollution is being under estimated by 24% on average (see Table 29), and although a big part of this percentage may be traced back to vehicle emissions, a 7.9% remains unaccounted for and may be due to under estimation of background NO_x levels from the DEFRA maps (Table 32)	Air pollution dispersion modelling and exposure assignment	Inaccuracy of air pollution and exposure (likely under estimation)	✗	Monitoring background data at numerous places of the city may offer more reliable measured data or a valuable dataset for the validation of models. However, to be feasible new air pollution monitoring technologies and/or the deployment of old cheaper ones e.g. diffusion tubes are needed at a large scale. Background air pollution modelling can further be improved e.g. undertaken at higher spatial resolution
			Health impacts modelling	Inaccuracy of health impacts (likely under estimation)	✗	
	TRAP maps resolution	- TRAP was estimated at a spatial resolution of 100 * 100 m grids - Levels of TRAP can vary significantly within tens of meters - An extension of this study showed that R^2 can drop by up to 29% when exposure estimates are made at the centroid of the 100x100m grid in which the validation point fell versus when the exposure estimates were made at the exact location of the validation points, see Khreis et al. (2017a)	Air pollution dispersion modelling and exposure assignment	Inaccuracy of air pollution and exposure	✗	Resolution of the maps or the air pollution estimates can be improved using actual addresses if known or estimating TRAP at finer grids for e.g. 10 m x 10 m. This would be feasible if coupled with improvements in the speed of calculations/processing of dispersion models such as ADMS-Urban
			Health impacts modelling	Inaccuracy of health impacts	✗	
Exposure-response functions assessment	Heterogeneity in underlying data	- There was significant heterogeneity in the underlying studies/data in terms of their quality, outcome definitions and phenotyping, age of participants, exposure assessments, pollutant studied and statistical methods - Heterogeneity in the meta-analysis differed depending on the pollutant studied - These factors all impact the strength and direction of the effect estimate - There was indication that part oof the heterogeneity may be explained by age of the child, see Table 3	Health impacts modelling	Inaccuracy of health impacts	✗	Heterogeneity should be further explored when more studies are available to pinpoint factors influencing exposure-response functions and effect sizes e.g. by sensitivity analysis or undertaking meta-regression grouping studies in similar groups based on their quality, outcome definitions and asthma phenotyping, age and sex of participants, exposure assessment methods etc. More standardization across study methods in the future can also provide insight into heterogeneity e.g. standard asthma definitions or exposure assessments
Health impacts modelling	Baseline incidence rates and outcome definition	- Baseline childhood asthma incidence rates were either scaled down to the population under study from national estimates or were obtained for the population under study but did not exactly match the explored age group - Further, definition of asthma differed and is expected to differ more with different datasets with the poor consensus on the definition of asthma - Using different definitions of asthma changed the burden of disease estimates considerably	Health impacts modelling	Inaccuracy of health impacts	✗	Other sources of baseline data can be consulted and compared to current estimates. Reporting at the local e.g. city and micro level e.g. neighbourhood or census tract is poor/missing and needs improvement by for e.g. using new technologies, integrated datasets, big data, encouraging or mandating reporting, working with health care providers to catalogue and report data. Some relevant initiatives are ongoing as part of the Born in Bradford cohort. Definition of asthma continues to be wide and more standard diagnosis practices are perhaps preferable

	as the number of the estimated attributable asthma cases drops by approximately 10% when using the first lower asthma incidence rate (123 per 10,000 person-year) whilst it increases by up to 223% when using the second higher asthma incidence rate (442 per 10,000 person-year)					

Table 43 Full-Chain Quantitative Health Impacts Modelling *Potential* Uncertainties, Likely Effects and Alternatives

Legend/ colour code

Traffic modelling stage

Emissions modelling stage

Air pollution dispersion modelling and exposure assignment

Health impacts modelling stage

Exposure-response functions assessment stage

Modelling stage	Uncertainty or error	Likely effect			Relative impact			Alternative(s)
		Description	Stage(s) of effect	Likely direction of effect	High	Moderate	Low	
Traffic modelling	Motorcycles	- Exclusion of motorcycles traffic (and emissions)	Emissions modelling	Under estimation of emissions			X	Including motorcycles percentages, models and emissions as specified in the NAEI and possibility of developing average-speed-emission functions for motorcycles in alternative versions of PHEM e.g. PHEMlight
			Air pollution dispersion modelling and exposure assignment	Under estimation of air pollution and exposure			X	
			Health impacts modelling	Under estimation of health impacts			X	
	Diurnal and seasonal effects (on traffic flows and speeds)	- The Bradford SATURN model only simulated traffic and speed data at 3 periods on an average weekday - Variations between the modelled periods was low and unrealistic - There are well known diurnal variations in traffic and speeds, as well as seasonal (e.g. weather) and ad-hoc (e.g. motor vehicle crashes) effects which are often not considered in traffic models - Traffic scaling was attempted but was limited as the Automatic Traffic Counters with full traffic data were few and no speed data was available	Emissions modelling	Inaccuracy of emission estimates		X		Continuous modelling or monitoring of traffic data to provide estimates that capture seasonal, diurnal and ad-hoc variations more accurately. If not possible, scaling procedure used in this study can be improved with more data sub-sampling at representative streets and at different times within a day and repeated over different days and seasons
			Air pollution dispersion modelling and exposure assignment	Inaccuracy of air pollution and exposure		X		
			Health impacts modelling	Inaccuracy of health impacts			X	
Emissions modelling	Age and maintenance of vehicles	- Vehicles age and maintenance including malfunctions, deterioration and tampering increase exhaust emissions - No such data was available for Bradford to account for vehicle age or maintenance conditions	Air pollution dispersion modelling and exposure assignment	Under estimation of air pollution and exposure		X		Data on vehicles' age and maintenance is not readily available and could be collected more systematically e.g. mean fleet mileage for different vehicle classes or prevalence of poorly maintained vehicles. Emissions degradation corrections are often applied to petrol and LDVs only although there is emerging evidence these are applicable to other fuels and classes. Traffic monitoring alternatives proposed above can also provide this data if designed accordingly
			Health impacts modelling	Under estimation of health impacts			X	
	Driving cycles underlying PHEM-based model	- The PHEM-based average-speed-emission functions were	Emission modelling	Inaccuracy of emission estimates			X	The driving cycles can be further expanded to cover more roads especially motorways and rural

		developed based on ≈ 30 hours of driving - This is perhaps not fully representative of driving conditions in the study area and did not cover enough motorway and rural roads (only 8 points with speeds > 50 km/h) - Further, the driving cycle was performed in one vehicle type (petrol Toyota Prius) which has different driving patterns and capabilities when compared to other vehicle classes including HDVs, buses and coaches	Air pollution dispersion modelling and exposure assignment	Inaccuracy of air pollution and exposure		✗	roads. The driving cycles can be undertaken using different vehicle types e.g. LDVs, undertaken by different drivers with different driving styles or can be collated indirectly by tracking different vehicle types e.g. buses or HDVs
			Health impacts modelling	Inaccuracy of health impacts		✗	
	Vehicle specifications underlying PHEM-based model	- Average vehicle specifications were used to parametrize the PHEM model - These came from London and Leeds data as no Bradford specific dataset was available	Emissions modelling	Inaccuracy of emission estimates		✗	Average vehicle specifications, directly observed in the study area, can be used in the future when data becomes available. Traffic monitoring alternatives proposed above can also provide this data if designed accordingly
			Air pollution dispersion modelling and exposure assignment	Inaccuracy of air pollution and exposure		✗	
			Health impacts modelling	Inaccuracy of health impacts		✗	
Air pollution dispersion modelling and exposure assignment	Meteorological data	- Only one meteorological station was used - 9% of meteorological data was missing	Air pollution dispersion modelling and exposure assignment	Inaccuracy of air pollution and exposure	✗		Ensuring better data capture can improve the dispersion and subsequent HIA estimates, especially if the missing data represent weather conditions dissimilar to the average. The full-chain models could be run again using data from different meteorological stations to test the sensitivity to meteorological data choice e.g. Leeds weather station
			Health impacts modelling	Inaccuracy of health impacts		✗	
	Built and natural environment features	- An average road width for all road links was assigned - The impact of street canyons, buildings, complex terrain and natural environment on the dispersion of air pollution and subsequent exposures was not considered	Air pollution dispersion modelling and exposure assignment	Inaccuracy of air pollution and exposure		✗	Integration with land-use and terrain data from Google Earth, GIS etc. can supply real-world data on the width of road links, street canyons heights and widths, surroundings building and natural environment and spatial changes in surface roughness. This data can be incorporated in more complex dispersion models' set-ups
			Health impacts modelling	Inaccuracy of health impacts		✗	
	Averaged exposures at the census tract level	- Exposure was averaged at the census tract level, regardless of size or population etc. - With this averaging, children mobility where relevant (i.e. at older ages), any effect of gender, ethnicity, socioeconomic differences on exposure, living in front or in the back of a building adjacent to roads, specific activity patterns e.g. time spent in census tract versus in other locations are not considered	Air pollution dispersion modelling and exposure assignment	Inaccuracy of air pollution and exposure	✗		The population mobility patterns can be obtained using travel surveys, diaries or personal tracking devices like GPS monitors. The activity patterns can be studied in relation to other influencing factors e.g. age, gender, etc. and averages derived. The activity patterns can be overlaid by air pollution maps and spatially varying exposure levels derived. Alternatively, different census tracts exposures can be used to account for durations spent in different areas and provide a composite exposure
			Health impacts modelling	Inaccuracy of health impacts	✗		

								estimate. The literature from other fields can be consulted
	NO_x to NO_2 conversion	- Dispersion model NO_x outputs were converted to NO_2 using one spatially constant factor - NO_2 varies spatially depending on proximity to source, vehicle fleet mix and ratio of primary NO_2, concentrations of O_3 and VOCs	Air pollution dispersion modelling and exposure assignment	Inaccuracy of health impacts	☓			More reliable vehicle specific ratios of primary NO_2 are needed and can be developed by collating measured emissions data e.g. remote sensing from the study area. These ratios can be used in the dispersion models using the chemistry option which further requires O_3 concentrations which were missing in the study area. Systematic collection of O_3 data is needed. Spatially varying NO_x to NO_2 conversion factors can be developed based on proximity to roads and possibly vehicle fleet mix
			Health impacts modelling	Inaccuracy of health impacts	☓			
Exposure-response functions assessment	Assuming a log-linear, no-threshold association between TRAP and asthma	- A (natural) log-linear association between exposure to TRAP and development of asthma was assumed in individual studies and subsequently in the meta-analysis which was conducted based on a continuous increase in the unit of exposure with no specified threshold under which no effect occurs - Studies reporting high versus low exposure analyses were very few and of limited power restricting their usability	Health impacts modelling	Inaccuracy of health impacts		☓		Future studies are recommended to systematically report categorical exposure analysis, alongside continuous exposure analysis. New methods capable of estimating the shape of the (potentially non-linear) exposure-response function can be explored and used in the individual studies
	Publication, reporting and status quo/ confirmation bias	- Studies with positive findings are more likely to be published and reported than studies with negative findings. The meta-analysis only included published studies - The included studies also overwhelmingly focused on certain well-studied pollutants e.g. NO_2 and less so or not at all on others e.g. BC and non-exhaust pollutants. This meant that some exposure-response functions were underlined with a sufficient number of studies (e.g. NO_2) whilst others were not (e.g. BC) - The literature was not evenly distributed geographically and was not globally representative with some regions being left out e.g. many developing countries	Health impacts modelling	Inaccuracy of health impacts			☓	Future meta-analysis could benefit from including unpublished studies or studies in other languages. Future research could focus on areas where the evidence is missing or not reported in English e.g. Africa and Asia notably including Middle East, Russia, Pakistan etc. and differences explored and highlighted. The focus on particular pollutants e.g. NO_2 should be expanded to other traffic-related pollutants including BC, NO_x, PM, UFPs, particles constituents and non-exhaust pollutants. Co-pollutant/multi-pollutant models can be useful in this context. Overview reviews of the global evidence are needed
	Effect of ethnicity, age and sex	- Ethnicity, age, and sex-specific exposure-response functions were not possible to generate due to lack of data and pooling the risk estimates for diverse subgroups in one value may distort the exposure-response functions and conceal true variability in	Health impacts modelling	Inaccuracy of health impacts			☓	More data on different responses between different ethnic groups, ages and genders is needed and the development of new specific exposure-response functions could follow. Stratifying analysis by these different factors may provide new insight

		responses and subsequent health impacts - Overall, there was no systematic evaluation of (susceptible) subgroups in the literature					
Health impacts modelling		-					
	Competing risk factors	- This is a generic limitation/uncertainty in HIAs. Asthma (disease) cases attributable to air pollution may well develop because of other competing risk factors e.g. genetic susceptibility, respiratory tract infections, exposure to allergens, chronic social and physiological stress, chemicals, unbalanced diet, co-morbidities, etc. - Typically, these factors are adjusted for in the underlying data from which the exposure-response functions were derived but some are not. On the other hand, protective factors may reduce the risk of disease with the exposure e.g. genetics, antioxidant intake etc. These factors are often not considered in the underlying data	Health impacts modelling	Inaccuracy of health impacts		✗	These relationships are not well understood and further research is needed for the development of more comprehensive and more realistic HIA models and methods. The adjustment for other competing factors in the underlying models is assumed to control this issue but protective factors are not well-studied

7.2.3. Implications for Policy and Practice

There are several policy implications of this work. First, this work provides comprehensive and robust evidence that (traffic-related) air pollution contributes to the development of asthma in children. The results indicate that the elimination or the reduction of traffic levels, TRAP and exposures can potentially prevent a considerable number of asthma cases from developing. The positive and statistically significant associations detected with the exposure to BC suggest a value of using this pollutant as an additional indicator in air quality monitoring and management. The attribution of incident asthma cases to TRAP has substantial implications for the burden of asthma-related exacerbations as well. As air pollution increases the risk of developing new asthma cases, then all future acute exacerbations of these cases, regardless of subsequent (immediate) causes of the exacerbations, should be again attributed to air pollution. This conceptual model has been previously followed in the literature where BoD estimates associated with air pollution were revised to account not only for asthma symptoms that are directly triggered by air pollution; but also for asthma symptoms triggered by other causes in children who developed asthma because of air pollution (Figure 71). The result was a significantly higher BoD estimate and perhaps a more realistic picture of the societal and economic impacts of air pollution (Künzli et al., 2008, Brandt et al., 2012). Largely, these impacts are preventable and there are numerous transport and land-use policy measures at the city level which can reduce the levels of and exposures to TRAP (Khreis et al., 2017e).

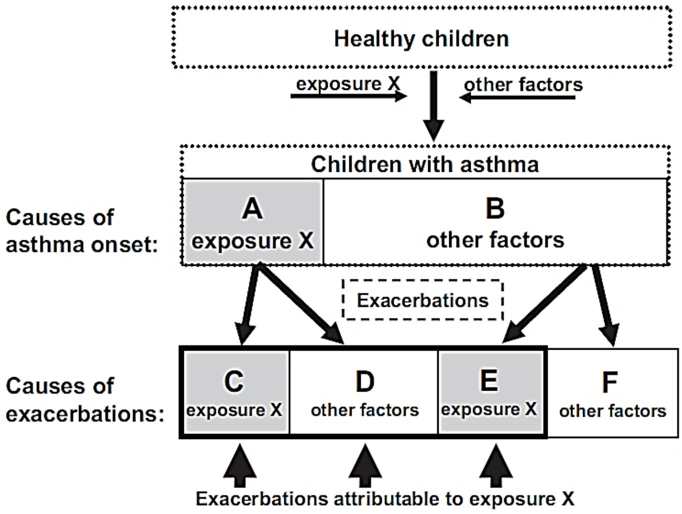


Figure 71 The burden of asthma exacerbations in children attributable to "exposure X," assuming a causal role of X in both disease onset and exacerbation.

Sizes of the boxes do not reflect the burden. The model starts with healthy children where some develop asthma due to X (A) or due to other causes (B). If X was the cause of asthma onset (A), all exacerbations among group A could be attributed to this factor X (C + D). Ambient air pollution is an example for "exposure X", Source: Künzli et al. (2008)

Second, this work demonstrated the discrepancy between real-world driving cycles as recorded in the Bradford's vehicle tracking survey and driving cycles as used in current and proposed type approval testing. This discrepancy echoes previous calls to adopt more realistic and more transient driving cycles for emission measurements and modelling (The International Council on Clean Transportation, 2015, Samuel et al., 2002, Barlow et al., 2009, Williams and Carslaw, 2011). Furthermore, as it stands the testing procedure and the emissions data underlying the development of widely used emission models do not account for road gradient, thermal windows' effects, air resistance etc. (Transport and Environment, 2013). Disregarding these factors, again, questions the reliability of current testing and modelling systems. Instead, vehicle emission testing could be undertaken on real roads to better account for real-world driving conditions such as road gradients, temperature, air resistance, etc.

Third, and linked to the optimistic and unrealistic laboratory testing procedures, is the emission under estimation of laboratory-based emission models such as COPERT, and PHEM. Currently, very few studies use full-chain exposure modelling to estimate the exposure to TRAP, but more of these models are needed to distinguish the effects of air pollution from traffic sources from the effects of air pollution from other sources. Nonetheless, estimates from full-chain exposure models are at the mercy of the emission factors inputted into these models (Barrat, 2013), and as shown, current emission factors are derived from laboratory-based emission models and are under estimated. The result is that dispersion models tend to systematically under estimate TRAP levels (Department for Environmental Food and Rural Affairs, 2010, Williams et al., 2011). Emission reduction projections based on these models also give an overly optimistic view of the likely future of road transport emission reductions (Carslaw et al., 2011b). When these estimates are used in subsequent health effects or health impacts analysis, errors are expected and associated health impacts are likely under estimated (Basagaña et al., 2013). This is significant as findings from epidemiological and health impact assessment studies can drive air quality and transport policies in the UK and elsewhere. On the shorter term, some correction or uplifting of the estimated air pollution and health impacts is needed; e.g. Peace et al. (2004). On the longer term, improvements in traffic modelling, emissions modelling (Table 42), and in background air pollution modelling and monitoring (Sayegh et al., 2016), are needed.

Fourth, vehicle emissions are often considered to be well understood and financial resources available for monitoring real-world emissions has been significantly reduced over the last years (European Research Group on Mobile Emission Sources, 2015). Going through the process of the present thesis, one can conclude that this is a short-sighted trend as there are numerous uncertainties associated with vehicle emission measurements and models. There is also a lack of real-world data that could potentially be used to validate, calibrate, enhance and develop existing and new vehicle emission models.

Finally, a policy relevant finding of this work was that the use of different average-speed-emission functions results in markedly different source apportionment. This finding demonstrates that source apportionment is sensitive to the emission modelling methodology adopted. In other words, different vehicle fleets are identified as the most polluting and contributing to TRAP, depending on how vehicle emissions are estimated. Therefore, the selected average-speed-emission functions affect which sources of road traffic emissions are targeted, with consequences for air quality and health, if the wrong source is targeted (Peace et al., 2004). These findings have particularly caught the eyes of CBMDC, who have recently obtained funding for upgrading their HGV and bus fleets (Khreis et al., 2016).

7.3. Final Thoughts

Air pollution contributes to the development of childhood asthma and is responsible for a substantial but preventable BoD. Full-chain quantitative HIA models provide valuable but underutilised tools to estimate the BoD associated with air pollution, whilst specifically disentangling the contribution of traffic to this burden. Such BoD estimates are relevant for numerous stakeholders as they provide defensible numeric indices of health risk factors, inform the health benefit-risk trade-off of public policies and provide the basis for mainstream economic evaluations such as cost-benefit analyses. As it stands, full-chain quantitative HIA modelling is in its early development and is a laborious and highly time-consuming process which carries numerous uncertainties, especially at the initial stages of traffic and emission modelling. The earlier the errors occur on the full-chain, the more influence they are likely to have on the final results. The feasibility, utility, validity and resolution of the full-chain quantitative HIA models and their supporting data need to be improved in the future. This can be done through the systematic collation, provision and verification of input data, the further validation of and improvements in the chain’s whole and distinct steps and the application of the modelling to real-life questions and scenario analysis, ideally with the participation of different disciplines and stakeholders.

Annex 5.1. UK Department for Environment Food and Rural Affairs NO_X Background Maps

Table 44 UK Department for Environment Food and Rural Affairs Background Maps Headers and Sectors – NO_x (Note that all traffic sources were excluded in the main analyses whilst minor roads and cold starts were included in one sensitivity analysis)

Headers included in main analysis	*Description*
Industry_in	Industry area in square sources (combustion in industry, energy production, extraction of fossil fuel and waste)
Industry_out	Industry area out square sources (combustion in industry, energy production, extraction of fossil fuel and waste)
Domestic_in	Domestic, institutional and commercial space heating in square sources
Domestic_out	Domestic, institutional and commercial space heating out square sources
Aircraft_in	Aircraft in square sources
Aircraft_out	Aircraft out square sources
Rail_in	Rail in square sources
Rail_out	Rail out square sources
Other_in	Other in square sources (ships, off-road and other emissions)
Other_out	Other out square sources (ships, off-road and other emissions)
Point_Sources	Point sources
Rural	Regional rural concentration

Headers excluded in main analysis	*Description*
Motorway_in	Motorway in square sources
Motorway_out	Motorways out square sources
Trunk_A_Rd_in	Trunk A roads in square sources
Trunk_A_Rd_out	Trunk A roads out square sources
Primary_A_Rd_in	Primary A roads in square sources
Primary_A_Rd_out	Primary A roads out square sources
Minor_Rd+Cold_Start_in	Minor roads and cold start in square sources
Minor_Rd+Cold_Start_out	Minor roads and cold start out square sources
Headers included in sensitivity analysis	*Description*
Minor_Rd+Cold_Start_in	Minor roads and cold start in square sources
Minor_Rd+Cold_Start_out	Minor roads and cold start out square sources

Annex 5.2. Snapped COPERT and PHEM-based Dispersion Models Validation

Table 45 Snapped COPERT and PHEM-based Dispersion Models Validation (rows) against Different Datasets (columns)

Models combination		Validation dataset: ESCAPE **NO_x** diffusion tubes (**n=41**)	ESCAPE **NO_2** diffusion tubes (**n=41**)	CBMDC **NO_2** diffusion tubes (**n=29**)	De Hoogh **NO_2** diffusion tubes (**n=48**)	CBMDC **NO_2** fixed-site monitoring (**n=8**)
Snapped COPERT-based dispersion model	COPERT dispersion model **NO_x** *at points* (varying background)	R^2= 0.30				
	COPERT dispersion model **NO_2** *at points* (varying background)		R^2= 0.33	R^2= 0.20	R^2= 0.59	R^2= 0.24
Snapped PHEM-based dispersion model	PHEM dispersion model **NO_x** *at points* (varying background)	R^2= 0.29				
	PHEM dispersion model **NO_2** *at points* (varying background)		R^2 = 0.32	R^2 = 0.10	R^2 = 0.52	R^2 = 0.003

Annex 6.1. Annual Average Census Tract Pollutant Levels Correlation Matrix

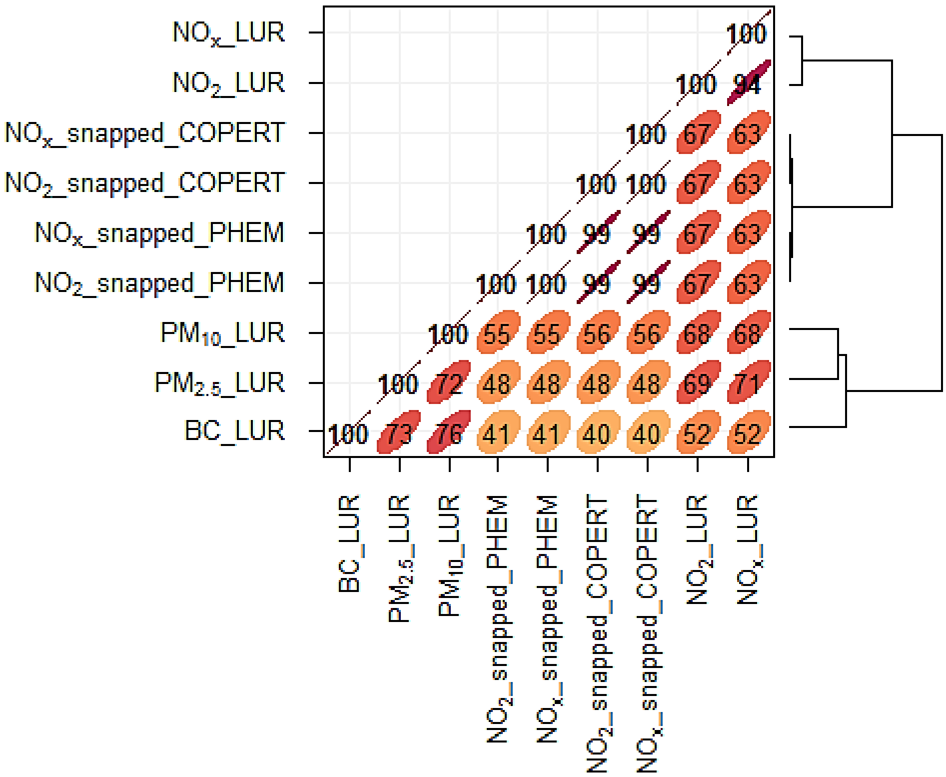


Figure 72 Matrix Showing Relationships (r) Between Different Pollutant and Model Combinations at Census Tract Level (µg/m³ for all Pollutants Except BC 10^{-5} M^{-1})

The ellipses can be thought of as visual representations of the scatter plots: a perfect positive correlation is drawn as a line at 45 degrees' positive slope. For zero correlation, the shape becomes a circle. The numbers in the ellipses are the correlation coefficients. The darker the colour; the higher the correlation.

Annex 6.2. TRAP-attributable Asthma Cases with Original (Unsnapped) SATURN Network

Table 46 Estimated Annual Attributable Asthma Cases in Bradford using the Original (Unsnapped) COPERT- and PHEM-based Dispersion Models (*baseline asthma incidence = 137 per 10,000 person-year, baseline asthma incident cases = 1827*)

Model	Attributable cases	Attributable cases lower CI	Attributable cases upper CI	Percentage of all cases
Original COPERT NO_2	**322**	139	428	**18%**
Original COPERT NO_x	**530**	-201	977	**29%**
Original PHEM NO_2	**318**	137	423	**17%**
Original PHEM NO_x	**524**	-198	968	**29%**

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