Assessing the contribution of road transport emission to air pollution and greenhouse gases in Africa: A disaggregate study in Kenya

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Abstract

Air pollution and greenhouse gas emissions affect health, climate and agriculture. In sub-Saharan Africa (SSA) air quality monitoring is underdeveloped which leads to uncertainty in the understanding of air pollution concentrations. However, studies that have been conducted in SSA show that ambient air pollution generally exceeds World Health Organization (WHO) guidelines. These studies show particularly high concentrations in urban areas such as Nairobi, Kenya. One of the key reasons is due to emissions from transport. Therefore, the main objective of this thesis is to quantify transport related emissions, set within the context of emissions from other sectors, using Nairobi, Kenya as a case study. Thus, this thesis has developed a methodology and framework at different scales (individual vehicle, city and national) to improve our understanding of transport-related emissions of air pollutants and greenhouse gas (GHG) to help guide policy making on future mitigation plans.

Road transport emissions were investigated at multiple scales; at the finest scale, particulate matter (PM) emissions from the tailpipe were measured for a few vehicles using a novel multiplexed portable measurement system. At the urban scale, a model for fuel economy was constructed for a fleet from data collected in the field. Finally, at the national scale, available data gathered on fuel economy, vehicle activity and emissions were integrated to provide a country-level assessment of air pollution and GHG emissions from road transport, including evaluation of transport policies to reduce air pollution and GHGs.

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Declaration

I declare that this thesis has been composed by myself and is all my own work except where explicitly indicated otherwise. This work has not previously been presented for an award at this, or any other, University. All sources are acknowledged as references.

Aderiana Mutheu Mbandi

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Chapter 1

1 Introduction

Air pollutants ground level ozone (O_3), sulphur dioxide (SO_2), nitrogen dioxide (NO_2), carbon monoxide (CO), particulate matter (PM), and lead (Pb) are designated as criteria pollutants as they are harmful to human health and environment (Suh *et al.*, 2000; WHO, 2006). In sub-Saharan Africa (SSA), exposure to particulate matter (PM) in ambient air is responsible for over 330 000 premature deaths annually (GBD, 2015; Forouzanfar *et al.*, 2016). The total cost of these deaths is estimated to be ~$215 billion (Roy, 2016). Greenhouse gas (GHG) emissions, CO_2, methane (CH_4) and ozone (O_3) and air pollutants such as black carbon (BC) also influence both global and regional climate (UNEP, 2011; Shindell, 2012; Klimont *et al.*, 2017). For Africa as a whole, the potential benefit by 2030 of implementing BC mitigation measures across all sectors has been estimated at 250 000 deaths avoided annually (UNEP, 2011; Shindell *et al.*, 2012).

The main cause of outdoor air pollution in SSA is emissions from combustion of fossil fuels used in industry, power generation, transport and domestic sectors (Schwela, 2012). Furthermore, emissions from burning of biomass fuel, waste open-burning and re-suspended dust from unpaved roads contribute significantly to air pollution in SSA (Liousse *et al.*, 2014; Lacey and Henze, 2015; Amegah and Agyei-Mensah, 2016; Marais and Wiedinmyer, 2016).

Few countries in SSA have the capacity and resources to establish and maintain long term ambient air quality monitoring (Odhiambo *et al.*, 2010; Schwela, 2012; Petkova *et al.*, 2013; Gaita *et al.*, 2014; Amegah and Agyei-Mensah, 2016; WHO, 2016), making SSA one of the least studied regions in terms of air quality (Doumbia *et al.*, 2012; Lourens, 2012). In addition there are limited epidemiological studies on impact of air pollution from Africa (Amegah and Agyei-Mensah, 2016). This leads to uncertainty in the understanding of air pollution concentrations in SSA.

However where studies have been conducted in SSA they have shown ambient air quality exceeds WHO guidelines for ambient PM (Petkova *et al.*, 2013). These studies conducted show particularly high pollution concentrations in urban areas such as Nairobi, Kenya. The evidence demonstrates that urban air pollution levels in SSA cities often exceed World Health Organization (WHO) annual guidelines of 10 µg/m^3 for particles of diameter less than 2.5 microns ($PM_{2.5}$), and 20 µg/m^3 for particles of diameter less than 10 microns (PM_{10}). A summary of these measured values for SSA cities are shown in Figure 1.1 and the ambient air quality standards are shown in Table 1.1.

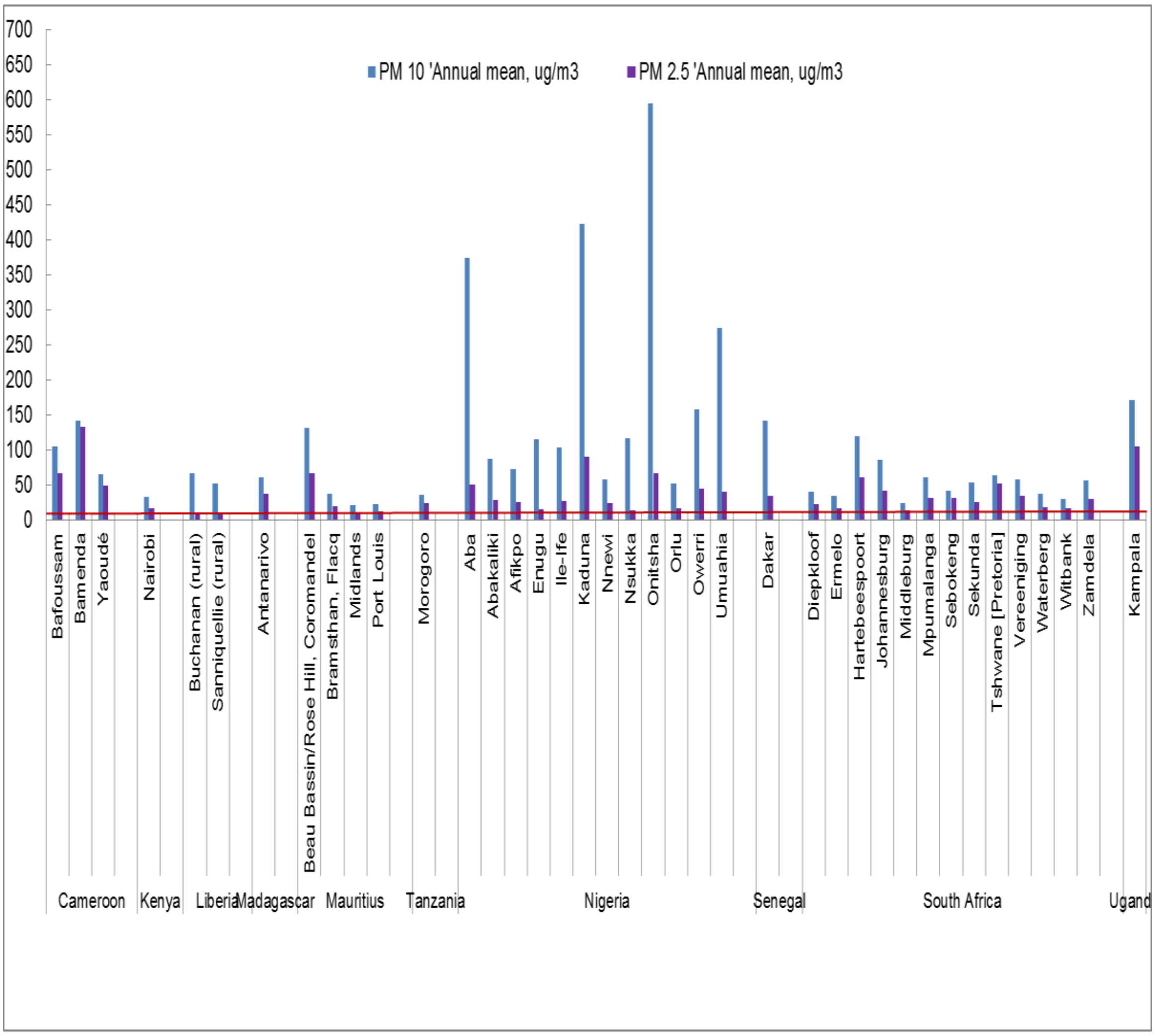


Figure 1-1: Measured PM_{10} and $PM_{2.5}$ for African cities, red line is the $PM_{2.5}$ annual mean WHO guideline for ambient air quality, (10µg/m^3). Source (WHO, 2015, 2016).

The ambient air quality monitoring studies summarised in Figure 1 come from a single station per city for periodic studies with the exception of those conducted in South Africa where a network of continuous monitoring sites exist (WHO, 2016). Therefore, most of SSA ambient air monitoring comprises short term measurements; this limits our understanding of the seasonal variation in pollution concentrations and only provides low density data that is inadequate for comprehensively evaluating air pollution models (Petkova *et al.*, 2013). The limited long-term systematic monitoring of ambient air quality in SSA results in poor support for policy formulation for air quality management which could aid in the reduction of air pollution levels and associated impacts (Schwela, 2012).

The number of deaths from PM air pollution in Africa has grown as the size of the urban population increases (Roy, 2016). This burden of air pollution will grow in the next 15 years as African cities are projected to account for up to 85% of the population (Kumar and Barrett, 2008; Ncube, 2012; UN-DESA, 2014). The majority of the urban poor in SSA dwell in informal settlements with poor living and environmental conditions, further worsened by air pollution which previous studies have shown to be higher in lower socio-economic status communities (Dionisio *et al.*, 2010; Volavka-Close and Sclar, 2010; Smitk and Akbar, 2012; Clark *et al.*, 2017).

Urban air pollution in SSA is on the rise, one of the key reasons is due to transport emissions (Doumbia *et al.*, 2012; Schwela, 2012; Petkova *et al.*, 2013; Liousse *et al.*, 2014; Marais and Wiedinmyer, 2016). The growth of SSA cities attributable to population growth and inward migration from rural to urban areas is increasing the demand for transport (Pirie, 2013). SSA cities are beset with urban sprawl that cause stress to an outdated and overburdened transport system that is under strain of congestion (Olvera *et al.*, 2013). Public transportation, shown to ease congestion and pollution in cities, is in a poor state in SSA because of inadequate investment, poor planning and deregulation (Kumar and Barrett, 2008; Assamoi and Liousse, 2010; Kinney *et al.*, 2011; Petkova *et al.*, 2013; Marais and Wiedinmyer, 2016; Behrens *et al.*, 2017). Public transport in SSA is mostly informal, made up of minibuses, vans, three-wheelers and motorcycles (Cervero and Golub, 2007; Assamoi and Liousse, 2010). Vehicle ownership in SSA is low compared to developed countries where motorization may have reached saturation levels (Dargay and Gately, 1999; Dargay *et al.*, 2007). However, vehicle ownership is increasing in SSA as those with disposable income import second-hand private cars and the use of motorcycles for public transport proliferates (Kumar and Barrett, 2008; Assamoi and Liousse, 2010; Marais and Wiedinmyer, 2016)

The increase in vehicle emissions because of rapid motorization in SSA, is exacerbated by an old vehicle fleet, high proportion of second-hand vehicle imports, poor maintenance, lack of regulation and/or implementation of vehicle and fuel standards, poor fuel quality and/or adulterated fuel, and poorly maintained and/or unpaved roads (Assamoi and Liousse, 2010; Kinney *et al.*, 2011; Petkova *et al.*, 2013; Liousse *et al.*, 2014; Marais and Wiedinmyer, 2016). Understanding the contribution each emission sector (including transport) makes to the pollution load is an important step towards developing urban air quality management plans. Unfortunately, the lack of data in SSA has made it extremely difficult to quantify the contribution of the transport sector to air pollution (Schwela, 2012; Petkova *et al.*, 2013). Kenya is one such country in SSA facing challenges of urban air pollution due to a rapidly growing vehicle fleet whose emission potential is largely unknown.

A review of published studies to ascertain the state of Kenya's air quality is summarised in Figure 1.2; sample averaging time of the measurements of $PM_{2.5}$, PM_{10} and BC are grouped by periods of less than 24 hours, 24 hours and annually. The air pollution measurements in Kenya highlight 4 key findings: the measurement studies carried out in Nairobi are predominantly short term studies with the exception of one annual study, PM concentrations regularly exceed WHO air quality guidelines (WHO, 2006), studies also highlight the concentrations are particularly high at roadsides and near roadways and mostly attributable to vehicle emissions (Gitari, 2000; Gatari *et al.*, 2005, 2013; van Vliet and Kinney, 2007; Odhiambo *et al.*, 2010; Kinney *et al.*, 2011; Gaita *et al.*, 2014; Shilenje *et al.*, 2016).

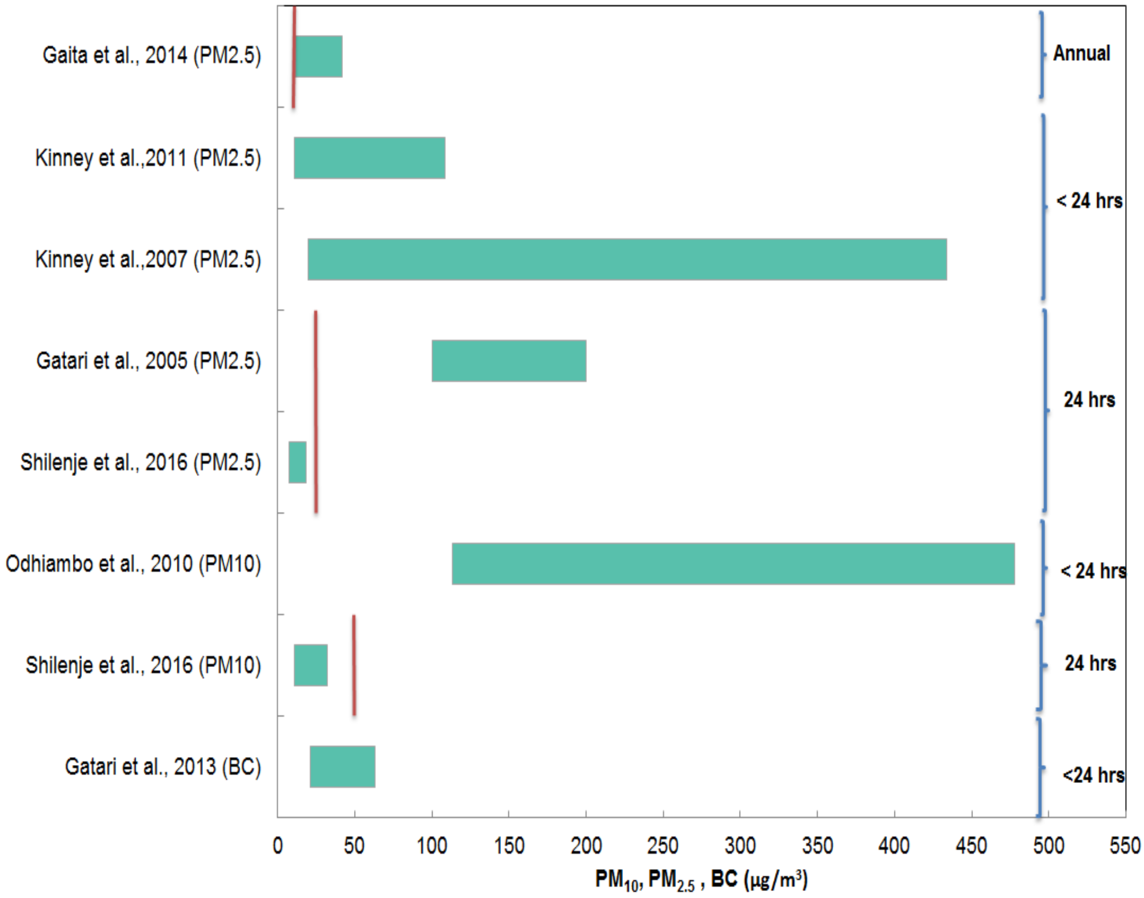


Figure 1-2: A summary of literature reported $PM_{2.5}$, PM_{10} and BC for Kenya for studies from 2000 to 2017. The red line is WHO guideline for $PM_{2.5}$ and PM_{10} annual and 24 hour limits in ambient air. The green bar represents the lower and upper range of $PM_{2.5}$, PM_{10} and BC concentrations in μg/m^3.

The highest PM values were measured at a roadside and registered a value of 239±126 μg/m^3 for PM_{10} as an 8 hour average (Odhiambo *et al.*, 2010). Similar results were found for $PM_{2.5}$ having a 22% higher 11 hour average concentration than sites located in the central business district (CBD) (Kinney *et al.*, 2011); the BC in $PM_{2.5}$ samples from roadside measurements was over 32 μg/m^3. Such concentration levels are in the range of values often found in megacities (with populations in excess of 10 million) emphasising the high pollution levels in Nairobi whose population is only between 3 to 4 million (Gatari *et al.*, 2013). Only one study (see Figure 2) found PM values to be less than the recommended WHO guidelines (Shilenje *et al.*, 2016). A long term study conducted for 33 months at two sites: an urban background site and a residential site, apportioned 39% of $PM_{2.5}$ sources as being traffic related (Gaita *et al.*, 2014). Based on the limited number of source apportionment studies, a tentative conclusion can be drawn that transport is a major source of $PM_{2.5}$ in Kenya (Gaita *et al.*, 2014). Therefore this thesis using Kenya as a case study will focus on quantifying transport emissions by developing new methodologies and insights that can be used to improve our understanding of transport related pollution and to guide policy making in future emission mitigation plans.

The framework developed for air quality management quantifies emissions using tools; emission inventories, dispersion models and exposure-effect relation models, to assess the impact of air pollutant concentrations and implement policy to reduce emissions (Schwela, 2012). In the framework, in order to mitigate air pollution impact on human health and environment, policies in the form of control measures legislation: air quality, emission standards are implemented (Schwela, 2012). In the transport sector these policies may include implementing better vehicle and fuel standards, increasing renewable energy use, investment in public transport to reduce number of vehicles (Bakker *et al.*, 2017). To assess the efficacy of implemented or proposed policy, scenarios are created against a reference to project plausible future considering observable present day conditions(Carter *et al.*, 2001). In this thesis, to understand the vehicle fleet and associated emissions in SSA, a review comparing the current international standards to SSA; ambient air quality standards, vehicle emission and fuel standards is presented.

1.1 Ambient air quality regulation and standards

World Health Organization (WHO) provides a set of guidelines for criteria pollutants for ambient air: PM, O_3, carbon monoxide (CO), sulphur dioxide (SO_2), nitrogen dioxide (NO_2) and lead (Pb) (WHO, 2006). A few SSA countries have adopted standards and regulations for these species in their outdoor air quality legislation (Lourens, 2012; Schwela, 2012; Shilenje *et al.*, 2016; Akinola *et al.*, 2017). Table 1.1, shows ambient air quality standards for South Africa (Department of Environmental Affairs, 2009, 2012) , Kenya (NEMA, 2014) and WHO guidelines (WHO, 2006).

Table 1-1: Ambient air quality standards for Kenya, South Africa and WHO ambient air quality guidelines (μg/m^3)

Pollutant	**Time Average**	**Kenya**			**South Africa**	**WHO**
		Industrial	**Residential, rural & other**	**Controlled Areas**		
SPM	Annual	360	140	70		
PM_{10}	Annual	70	50	50	40	20
	24 hours	150	100	75	75	50
$PM_{2.5}$	Annual	35			25	10
	24 hours	75			65	25
NO_2	Annual	150			40	40
	24 hours	100			200 (1 hr)	200 (1 hr)
Pb	Annual	1	0.75	0.5	0.5	0.5
SO_2	Annual	80	60	15	50	20 (24 hr)

Outdoor air quality standards in Kenya have higher limits compared to WHO and South Africa. They are grouped into three areas: industrial, residential and rural and controlled areas with the strictest standards been applied to the controlled areas followed by residential areas. Controlled areas are hospitals, national parks, reserves, sanctuaries and central business districts (CBD). For industries in designated residential areas, the stricter residential standards will apply, but for residential premises in designated industrial areas, the residential standards do not apply. However, the responsible authority can designate any area as controlled.

1.2 Vehicle emission and fuel standards

Road transport sector (passenger cars, light commercial, buses, heavy duty vehicles, motorcycles and three-wheelers) emissions due to fossil fuels burned (diesel and petrol) include sulphur dioxide (SO_2), nitrogen oxides (NO_X), carbon dioxide (CO_2), carbon dioxide (CO), methane (CH_4), non-methane volatile organic compound (NMVOC), PM, BC, organic carbon (OC) and ammonia (NH_3). In addition to health effects of PM (GBD, 2015; Forouzanfar *et al.*, 2016), primary pollutants, NO_X and NMVOC react in the atmosphere to form O_3, a secondary pollutant affecting human health and vegetation and crop yield (Van Dingenen *et al.*, 2009; Lim *et al.*, 2012). BC and CH_4 from road transport and O_3, are projected to have a significant impact on climate change in the next 20-40 years (UNEP, 2011). Therefore, mitigation measures combining CO_2, BC and CH_4 reduction will greatly improve the chances of keeping the earth's temperature to below 2 °C (Shindell *et al.*, 2011; UNEP, 2011). A substantial part of PM is made of BC and OC (UNEP, 2011) and in urban areas in SSA, traffic can responsible for up to 88% of BC (Doumbia *et al.*, 2012). Table 2 shows the type of pollutants from road transport.

Table 1-2: Type of vehicle pollutants (Faiz *et al.*, 1996; Ntziachristos *et al.*, 2013).

Class of pollutants	**Name of Pollutants**
Ozone (O_3) precursors	CO, NO_X, NMVOC, CH_4
Greenhouse gases	CO_2, CH_4, nitrous dioxide (N_2O)
Short Lived Climate Pollutants (SLCP)	Black carbon (BC), CH_4
Acidifying substances	NH_3, SO_2, NO_2
Particulate matter	PM_{10}, $PM_{2.5}$
Carcinogenic species	Polycyclic aromatic hydrocarbons (PAHs) Benzene (C_6H_6)
Toxic substances	dioxins and furans
Heavy metal	lead, arsenic, cadmium, copper, chromium, mercury, nickel, selenium and zinc

Vehicle standards cannot be decoupled from fuel standards (Walsh, 2014), as certain vehicle technologies require a specific fuel quality standard. This is exemplified in Figure 1.3, where fuel quality (shown here as diesel sulphur content) is matched to the European vehicle emission standard (Euro1 to Euro 6) and the vehicle emission reduction technology.

Stringent vehicle emission standards are considered an effective instrument to achieve reductions in emissions in two ways: i) the automotive industry develops new technologies to meet the standards ii) refineries improve fuel standards to meet the automotive sector demand. Vehicles in developed countries have advanced vehicle technology and high fuel quality. The turnover of the vehicle fleet in developed countries is high with many of the obsolete vehicles being exported to developing countries; accordingly, the health effects associated vehicle emissions have shifted to developing countries (Chambliss *et al.*, 2013; Klimont *et al.*, 2017).

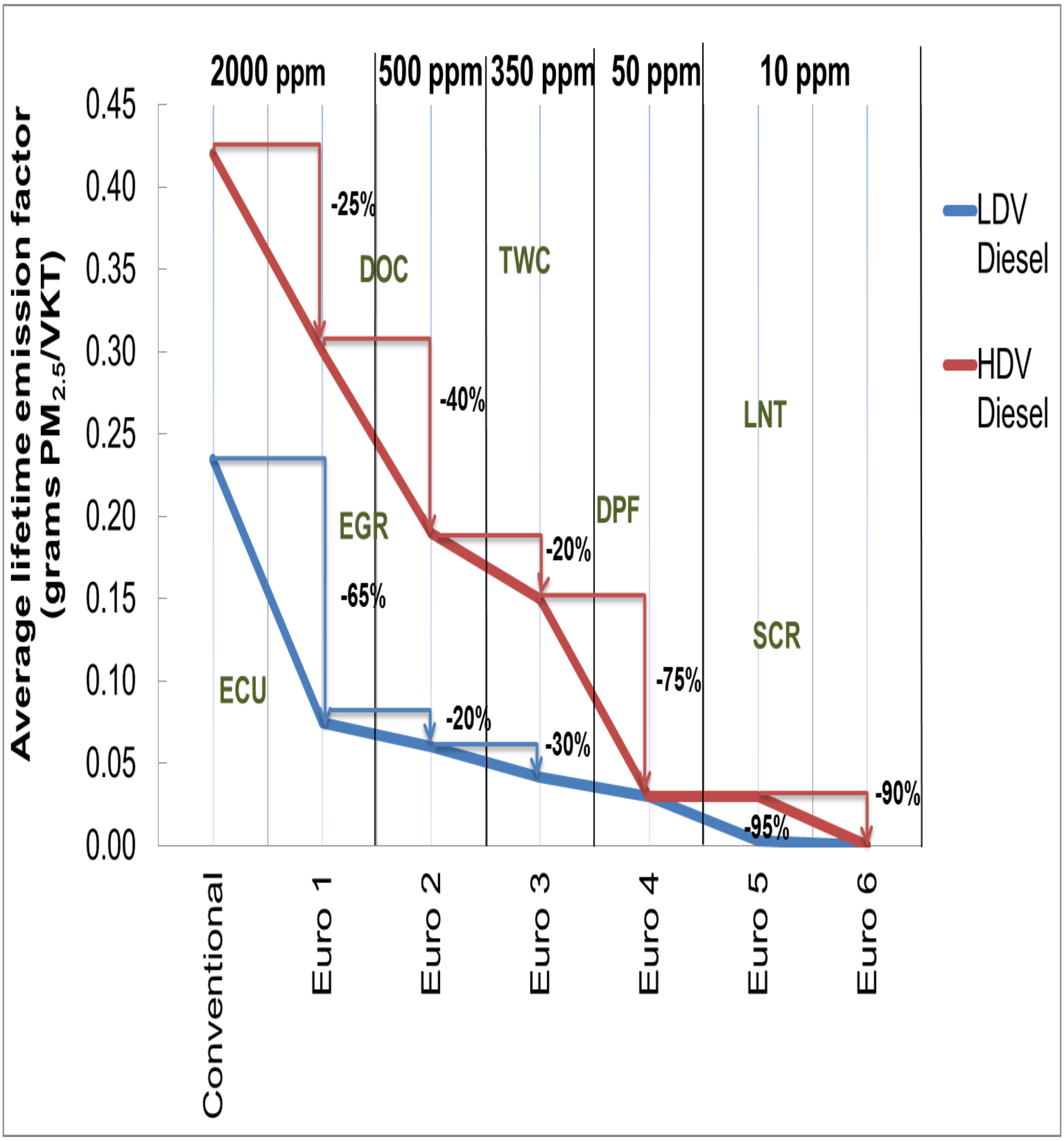


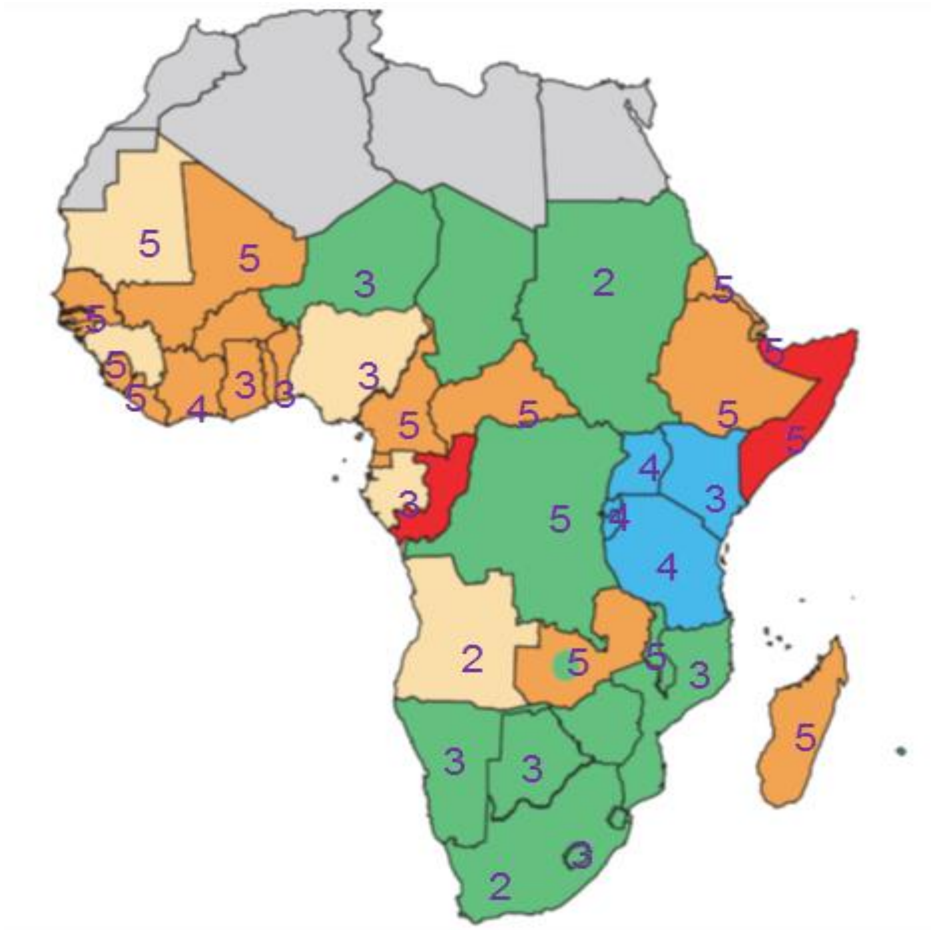
Figure 1-3: Fuel quality for diesel light duty vehicles (LDV) and heavy duty (HDV), vehicle emission reduction technology and PM emissions adapted from (Chambliss *et al.*, 2013). DOC: Diesel oxidation catalyst, ECU: Engine Control Unit, EGR: Exhaust Gas Recirculation, TWC: Two-way catalytic converter, DPF: Diesel Particulate Filter, LNT: Lean NO_X traps, SCR: Selective Catalytic Reduction.

Low sulphur content ensures vehicles with emission control devices operate optimally reducing PM emissions in addition to reducing SO_2 emissions. Emission reduction technologies, combined with ultra-low sulphur diesel or petrol can reduce PM emissions by up to 99% (Chambliss *et al.*, 2013) (see Figure 1.3). In developed countries over 25 years, sulphur in fuel dropped from 2000 ppm to 10 ppm sulphur in diesel, at the same time emission reduction technologies such as diesel oxidation catalyst (DOC), diesel particulate filters (DPF), exhaust gas recirculation (EGR), selective catalytic reduction (SCR) and lean NO_X traps to reduce the air pollutants (CO, NO_X, PM), GHG (CO_2) and BC were installed in vehicles. DPF and gasoline particulate filters (GPF) introduced post 2000, together with SCR reduced 75% of fine PM (Mamakos *et al.*, 2014).

In SSA, some countries have low sulphur limits for diesel fuel quality, represented in green in Figure 1.4. The trading region of East Africa Community (EAC) and Southern Africa Developing Cooperation (SADC) each has between 50 and 500 ppm sulphur limits for diesel fuel. The East African region harmonised their fuel quality, giving a sulphur limit for petrol of 150 ppm, and for diesel of 50 ppm (KEBS, 2007, 2010, EAC, 2011a, 2011b). This was implemented in 2016, and resulted in a 10-fold improvement on previous fuel quality standards.

By contrast to fuel quality regulations, there are only very few vehicle emission regulation and limits in SSA. A few countries rely on limiting the age of the vehicle (year of manufacture) on vehicle importation (UNEP-PCFV, 2014; Lacey *et al.*, 2017). In addition to the penetration of low sulphur diesel, Figure 4 also shows vehicle standards for light duty vehicles for various African countries.

The lack of domestic automotive manufacturing capacity is linked to the large scale import of second-hand vehicles in SSA. For example, only South Africa has a significant automotive sector in SSA (Holmes, 2013; IEA, 2017). As shown in Figure 4, South Africa is also one of the SSA countries with strict vehicle regulations as they have mandatory standards for new vehicles. South Africa introduced emission specifications for all new vehicle models in 2005-2006, and as of 2008, all new vehicles sold need to comply with the modified Euro 2 emissions specifications (SAPIA, 2008). In East Africa, almost all vehicles are imported second-hand from Japan through the gulf states (Kumar and Barrett, 2008; ERC, 2015b). The minibuses and buses (*matatus* in Kenya) are imported as light to medium truck chassis, with the body of the vehicle being locally constructed and mounted (Kumar and Barrett, 2008).



Fuel Quality-Diesel Sulphur	Vehicle Standards for Light Duty Vehicle (LDV)	
15 & below*	Import of used cars not allowed	1
>15-50	Import of used cars not allowed-exemption	2
>50-500	Import of used cars allowed-Age limit or vehicle mileage cap	3
>500-2000	Import of used cars allowed-Tax regime	4
>2000-5000	Import of used cars-No restriction	5
>5000 & Above	Unknown	6
* Information in parts per million (ppm)		

Figure 1-4: Map of Africa with fuel and vehicle standards adapted from (UNEP, 2015)

However, in SSA, there is a lag and thus a mismatch between available fuels, (i.e. unleaded and with low sulphur content) and vehicle standards. In Figure 1.4, East Africa has fuel standards to meet Euro 4/IV vehicle standards but there exists minimal vehicle standards (pre-Euro standards), for Kenya there is at least an age limit cap of 8 years on vehicle imports (ERC, 2015b), which means imported vehicles should be at least Euro IV/4 equivalent . South Africa is set to introduce Euro 5, however the date is not yet set (Venter, 2008; Droppa, 2012; Anderson, 2013). Nigeria has Euro II mandatory vehicle standards, a regulation introduced in implemented in 1996, and they are looking to introduce Euro 3 standards in January, 2015 (Loveday, 2011), however the fuel standards do not match this standard. Other SSA countries in general have import restrictions for used vehicles based on age, technology and mileage of the vehicle, but these are few as the majority of SSA countries do not have mandatory vehicle standards and even less have vehicle emission limits for vehicles (Schwela, 2012; UNEP-PCFV, 2014).

Rapid increase in SSA countries of unregulated import and use of motorcycles (called *bodaboda* in East Africa) and 3-wheelers (called *tuk-tuk* in East Africa) for public transport is affecting health in two ways, increased motorcycles related accidents (WHO, 2013) and heavy pollution (Assamoi and Liousse, 2010). Motorcycles are major sources of particulate matter (PM), hydrocarbons (HC), carbon monoxide (CO) and other hazardous emissions resulting from the release of burned and unburned lubrication oils (USAID, 2000). In a previous study in Egypt it was shown PM emissions of a single two-stroke motorcycle were equivalent to one diesel-powered bus or truck; the HC emissions were equivalent to 10 petrol vehicles. By contrast, four-stroke motorcycles (which are more common in developed countries), emit only slightly more pollutants than small petrol vehicles (USAID, 2000).

Fuel economy standards decrease emissions by reducing fuel consumption per vehicle mileage (Plotkin, 2016) i.e. the volume of fuel consumed per km is reduced. Most of SSA countries do not have fuel economy standards, apart from South Africa's carbon tax on newly registered light duty passenger vehicles that are above 120 g CO_2/km (5.2 l/100 km) (IEA, 2017). However, the benefits of this carbon tax in South Africa are likely offset by the large percentage of a fleet that is old (Letshwiti *et al.*, 2003; Merven *et al.*, 2012), and whose fuel economy is poor. Kenya does not have fuel economy standards, a previous study on fuel economy standards for light duty vehicles showed a worsening fleet fuel economy for the new fleet even though the average age was only about 8 years old (ERC, 2015b). This was possibly due to the increasing number of sport utility vehicles (SUVs) imported from 2010 to 2011. However, this study had limitations as it was confined to newly registered light duty vehicles (2010 to 2012), and in the absence of Kenyan fleet fuel economy data, EU and USA fleet fuel economy values were used.

Vehicle emission standards governing limits, inspection and maintenance (I/M) for vehicles are extremely rare in SSA (Schwela, 2012). For Kenya, even though vehicle emission standards are specified in KS1515 (KEBS, 2014), (see Table 1.3), they are not enforced (Cameron *et al.*, 2012; ERC, 2015b). According to the Kenyan ambient air quality standards, priority pollutants from mobile sources (including vehicles) are HC, VOC, SO_X, PM and CO (NEMA, 2014). Under KS1515, vehicle emission inspection should be undertaken for all commercial and public vehicles annually and for every private vehicle more than 5 years old biennially. The environment agency or motor vehicle inspection unit (MVIU) may order any vehicle with visible exhaust emissions to be inspected. On the other hand, Rwanda for example has implemented vehicle emission limits and enforced inspection since 2015 (Government of Rwanda, 2014). Commercial vehicles undergo inspection biannually and private cars annually. South Africa has implemented Euro 2 standards for new vehicle models since 2006 (Delphi, 2017), however inspection limits and inspection of in-use vehicles is carried out at the municipal level and therefore under municipal air quality by-laws. For example, the City of Cape Town has limits for diesel vehicles, 56 Hartridge smoke units (HSU) or 1.61m $^{-1}$ for turbocharged engine (City of Capetown, 2010), this is lower than Kenya's limit for a similar engine (see Table 3).

Table 1-3: Vehicle emission exhaust limits for Kenya from KS1515 standard

Petrol vehicles				
Year of manufacture	**CO standard (%)**	**HC standard (ppm)**	**lambda (λ)**	Type of test
1986-1992	3.5	1200		Idle
1992-1994	3.5	1200		Idle
>1995	3.5	1200		Idle
>1992	0.5		1±0.03	2 speed idle (>2500rpm)
Diesel vehicles				
Year of manufacture	Turbocharged	Naturally aspirant	Test of test	
< 1979			Visual	
> 1980	3.0 m $^{-1}$	2.5 m $^{-1}$	free acceleration	

National emission inventories are compiled using emission models which require emission activity of the different sectors and emission factors for the different pollutants (Kousoulidou *et al.*, 2013). For the road transport sector, vehicle emission factors are determined through tailpipe emissions, these are influenced by a variety of factors which include fuel quality and technology (shown in Figure 1.3), vehicle type, fuel type, size of engine, road grade, transport infrastructure, weather conditions and traffic conditions (Zhang, 2006; Chambliss *et al.*, 2013; Franco *et al.*, 2013). Emission factors may be measured in the laboratory on a chassis dynamometer over a driving cycle (Frey *et al.*, 2003; Zhang, 2006; Franco *et al.*, 2013; Kousoulidou *et al.*, 2013), by remote sensing, where pollutants in a real-world vehicles emission plume is determined through spectroscopy (Jiménez-Palacios, 1999; Carslaw and Rhys-Tyler, 2013; Carslaw *et al.*, 2013) and by on-road emissions testing using portable emission monitoring systems (PEMs) (Frey *et al.*, 2003; Weiss *et al.*, 2011, 2012; Huang *et al.*, 2013), to measure for exhaust gases and particulates. Of these different methods, the dynamometer tests do not reflect real-world conditions (Zhang, 2006; Weiss *et al.*, 2011, 2012; Franco *et al.*, 2014; Thompson *et al.*, 2014; Kuranc, 2015; Degraeuwe and Weiss, 2016).

Remote sensing is a rapid way to measure exhaust emissions for large number of vehicles, and can be especially useful in detecting a small percentage of heavy polluters that are problematic contributors to pollution in developed countries (Jiménez-Palacios, 1999), It's applicability in SSA is as yet untried. Ultimately, very few tailpipe emission measurements are carried out in SSA because of a lack of resources and technical capability, yet the higher pollutant emissions likely to be associated with typical SSA vehicle fleets increases the need for tail-pipe emissions measurement to be carried out under real-world conditions in SSA.

1.3 Problem statement

Lack of emission data has made it extremely difficult to quantify the contribution of the road transport sector to air pollution. Transport emission inventories compile data on vehicle fleet and associated emission factors to estimate the air pollution contribution. Emission inventories have been identified as one of the tools required for air quality management as they permit implementation and enforcement of air quality measures which are lacking in SSA (Schwela, 2012).

Transport emission estimates have large uncertainties in SSA as they lack adequate data essential to build accurate inventories (Assamoi and Liousse, 2010; Liousse *et al.*, 2014; Marais and Wiedinmyer, 2016). These data need to be disaggregated to different vehicle types includes; total number of vehicles, activity data such as fuel consumption and vehicle mileage, fuel share and region specific emission factors. Poor record keeping reduces the accuracy of the number of in-use vehicles for particular vehicle types such as motorcycles (Assamoi and Liousse, 2010; Kumar, 2011), minibuses (Graeff, 2008). Traffic and travel surveys which provide activity data and vehicle characteristics are also lacking in SSA (Cameron *et al.*, 2012; Salon and Aligula, 2012; Venter and Mohammed, 2013; Liousse *et al.*, 2014). There are also limited field measurements to determine emission factors for on-road vehicles (Lents *et al.*, 2004; Goyns, 2008; Liousse *et al.*, 2014). Furthermore, country level data when available, is based on limited studies which are extrapolated to the rest of the country or in some cases the continent (Marais and Wiedinmyer, 2016). In addition, further uncertainties are introduced due lack of data on the location of paved and unpaved roads to estimate road dust emissions from the transport sector (Marais and Wiedinmyer, 2016).

The International Vehicle Emission (IVE) model funded by US Environmental Protection Agency (EPA) developed for estimating emissions in developing countries was previously used to estimate tail-pipe vehicle emissions in Nairobi in 2002 (UC Riverside, 2002; Lents *et al.*, 2004, 2005). This 2002 study consisted of a video survey and parking lot survey (UC Riverside, 2002). The video survey was conducted to determine vehicle count per day on different roads, where it was determined that passenger vehicles accounted for over 80% of the vehicle fleet. Parking lot surveys were also conducted to gather information on parked vehicles including licence plate, odometer readings, transmission type and vehicle condition. On-road estimation of emission factors using PEMs equipment was carried out in Nairobi for passenger vehicles (Lents *et al.*, 2005), based on the recommendations of an initial estimate of vehicle emission rates for Nairobi and other cities (Lents *et al.*, 2004). However, there were limitations with this approach. Firstly, most of the vehicle information obtained through the parking lot survey was subjective, for example, a judgement call was made on the condition of the vehicle, fuel type and the technology of the vehicle. Secondly, other critical information was not available, for example, odometer readings were not available for vehicles models manufactured post 2001 (these odometers are digital and only display if the vehicle is switched on). Thirdly, license plates were recorded and used as proxy for age of the vehicle, this is unlikely to be accurate for most of SSA where vehicles are second-hand when sold or imported already in a reconditioned state. Furthermore, in Kenya, the licence plate number is allocated on registration possibly on importation, so newer plates are not always indicative of new vehicles. Finally, although the IVE model is specifically designed for developing countries, it is still quite complex and requires high density input data (Nagpure and Gurjar, 2012), data that countries in SSA are lacking.

A limited number of SSA countries have detailed national transport inventories. A previous study in Kumasi, Ghana, showed an increase of GHGs, PM and NMVOC between 2000 and 2005 from vehicles, using the COPERT III model (Agyemang-Bonsu *et al.*, 2010) . COPERT is an emission model developed for the European Environment Agency (EEA) and used widely in Europe and non-European countries to quantify road transport emissions (Kholod *et al.*, 2016). In South Africa, a detailed energy transport inventory showed energy demand and CO_2 emissions doubling in a business as usual scenario by 2050 (Merven *et al.*, 2012). Both of these models require high emission and activity data which other SSA countries may find difficult to access. It is also valuable to evaluate the accuracy of these models compared to actual emission measurement (Guo *et al.*, 2007).

The transport sector in Kenya at present lacks a detailed national transport emission inventory for all pollutants and thus cannot evaluate the impact of different policies to reduce emissions. This thesis's contribution and novelty is the filling of these transport emission data gaps with an approach that is less demanding with respect to data requirements; developing novel methodologies to collect the data, creating predictive models using the data collected, building a framework in which this data can be used for an assessment of how transport emissions can be reduced and demonstrates its effectiveness in transference to other SSA countries facing similar challenges.

1.4 Research objectives

The work of this thesis aims to overcome these data limitations with a view to improving the quantification of the contribution of transport emissions to air pollution in SSA. The thesis will focus on Kenya, developing and testing methodology, collecting and analysing data describing vehicle fleet at different scales. At the macro-scale level, national level emissions are estimated using aggregated activity data for vehicle fleets such as vehicle kilometres travelled (VKT) and emission factors. At the meso-scale, urban emissions are estimated using aggregated activity data but with a higher resolution than macro-scale. Finally , at the micro-scale individual tail-pipe emissions are estimated with high temporal and spatial resolution (Zhang, 2006). The following main objectives are defined:

- Demonstrate a simple protocol for an inexpensive portable emission monitoring system (PEMS) measurement system that can be rapidly deployed to determine tail-pipe emissions at the micro-scale in a real-world challenging environment.
- Develop capabilities for measuring, estimating and modelling for in-use urban fleet vehicle activity and fuel economy for Nairobi.
- Develop a national emissions inventory for Kenya to estimate the transport contribution to total emissions in the context of emissions from other sectors.
- Combine the output from the first three objectives to estimate the road transport sector contribution to total emissions and evaluate the impact of different policies to reduce emissions at the national level.
- Develop a framework in which the emissions data from the four objectives can be used for an assessment of how road transport air pollution and GHGs can be reduced in Kenya.

1.5 Organization of the thesis

This dissertation consists of five chapters with the main body comprised of 3 journal papers in Chapter 2, 3, and 4. One of the manuscripts has been submitted (chapter 3) and the other two are ready to be submitted. There is a combined reference list at the end and for each chapter of the dissertation, there is separate supporting information.

This Chapter 1 describes the background of the thesis. Here the status and potential consequences of ambient air quality in SSA, with a focus on Nairobi, are described. Also described are the policy tools that try to improve air quality across SSA; specifically the standards and regulations governing ambient air quality and the vehicle emissions and fuel standards that influence pollutant emissions from the transport sector. The rationale for the research conducted in this thesis is then laid out as a problem statement, the research objectives are stated followed by this description of the organization of the thesis.

Chapter 2 presents a detailed description of the instrumentation, experimental design and statistical analysis for the estimation of real-world measurement of tail-pipe emissions of vehicles in Nairobi, Kenya. The paper in chapter 2 is titled, “Evaluating real-world vehicle particulate matter emissions using a novel multiplexed portable instrument in a challenging African urban environment”.

Chapter 3 is the development of a methodology to collect vehicle activity (mileage, fuel consumption) and vehicle characteristics (age, weight , engine size) that tests the applicability in a data-poor environment, the outputs of these data collected is used to estimate fuel economy and vehicle activity data. The paper in chapter 3 is titled, “Estimating vehicle fuel economy in Africa: A case study based on an urban transport survey”.

Chapter 4 is the compilation of a national emissions inventory and evaluation of the contribution of road transport emissions to Kenya's air pollution and GHG emissions. The paper in chapter 4 is titled, "Assessment of the impact of road transport policies on air pollution and greenhouse gas emissions in Kenya".

Chapter 5 is a synthesis of the thesis showing how the research of each chapter comes together to form a coherent body of knowledge.

This chapter gives an overview including the background on the thesis, summarises the justification and rationale for undertaking the thesis and then states the objectives and research questions and finally lists the organization of the thesis.

Chapter 2

The work outlined in this chapter has been adapted from a research paper prepared for publication. Dr Karl Ropkins and Dr Martin Weiss contributed to the formulation of the methodology. I undertook all data analysis, but Dr Chris Malley helped to write the algorithm for calculations of the vehicle emissions variables. Dr Martin Weiss, Dr Chris Malley, Dr Karl Ropkins and my supervisors, Dr Lisa Emberson, Dr Harry Vallack and Dr Dietrich Schwela following an initial draft, made valuable contribution to the methodology, presentation of results and discussions through consultations and manuscript editing.

2 Evaluating a novel multiplexed particulate matter system to measure real-world emissions and driving pattern of light-duty vehicles in an African urban environment

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Abstract

In African cities road transport is a major contributor to air pollution. Although part of the fine particulate matter ($PM_{2.5}$) concentrations in urban areas can be attributed to diesel vehicles, there is still a lack of measurements that assess PM on-road emissions and operating pattern of vehicles in these environments. This paper details a simplified methodology for the evaluation of a real-world tail-pipe PM emissions measurement system in an urban environment. The focus is on light-duty diesel passenger vehicles which were equipped with a prototype multiplexed Portable Emissions Measurement system (parSYNC®-PEMS) comprising of three sensors (ionization, opacity and scattering) in combination with standard analytical equipment. Tests were performed on a 52 km test route around Nairobi (Kenya) covering urban, highway and peri-urban roads. We find that for 75% of the time, parSYNC®-PEMS had a higher voltage for all sensors during acceleration as compared with idling and deceleration. At 91-94% of the time, the tested vehicles were operated in a vehicle specific power (VSP) of between -15.2 and 17.7 kW ton^{-1}, which is typical for heavily congested traffic at high altitude with steep roads. The results show a clear relationship between sensor voltage and VSP.

Turbocharging was found to dramatically increase the sensor output voltage. Although preliminary, it may be possible to implement this method to monitor emission trends using multiple sensor voltage which is indicative of PM emissions. This will aid to quantify real-world emissions of various fleets in a challenging African urban environment. However, additional evaluation of this instrument is necessary since the protocol did not include calibration with a reference instrument or collection of data from more vehicles for statistically sufficient data.

Keywords

Transport, Africa, Diesel, Particulate Matter (PM), Real-world, In-use, Air Pollution, PEMS, VSP

2.1 Introduction

Particulate matter (PM) is a major cause of ill health and premature deaths around the world; it is also a contributor to regional and global climate change (Anenberg *et al.*, 2012). In Africa, outdoor air pollution is estimated to cause over 330,500 premature deaths each year (Forouzanfar *et al.*, 2016). In urban areas, road traffic contributes substantially to PM in the particle size range of less than 2.5 µm ($PM_{2.5}$) (Pant and Harrison, 2013); yet only a few studies apportion the contribution of emissions from vehicles to $PM_{2.5}$ air pollution in Africa.

Where such studies have been conducted they have found contributions of 42% by diesel vehicles in Cape Town and 39% by overall traffic in Nairobi (Wicking-Baird *et al.*, 1997; Gaita *et al.*, 2014). Developing accurate vehicle emissions inventories plays, therefore, an important role for air quality management (Zhang, 2006; Goyns, 2008; Schwela, 2012; Kousoulidou *et al.*, 2013). A key requirement of such inventories are vehicle emission factors (EF); these tend to vary with, e.g., fuel and vehicle type, engine size, weight, vehicle age and technology (specifically after-treatment technology), driving pattern, road gradient, and general maintenance (Zhang, 2006; Chambliss *et al.*, 2013; Franco *et al.*, 2013; Choudhary and Gokhale, 2016).

Emission factors can be derived using two approaches. First, vehicles can be driven over pre-defined cycles on a dynamometer in the laboratory (Frey *et al.*, 2003; Zhang, 2006; Kousoulidou *et al.*, 2013; Kuranc, 2015). These laboratory tests are expensive (Goyns, 2008; Posada and German, 2013), and results obtained have been shown not to reflect real-world condition (Zhang, 2006; Weiss *et al.*, 2011, 2012; Franco *et al.*, 2014; Garcia, 2014; Pillot *et al.*, 2014; Thompson *et al.*, 2014; Kuranc, 2015; Degraeuwe and Weiss, 2016; FIA, 2017). Laboratory tests are also vulnerable to manipulation by defeat strategies (Thompson *et al.*, 2014; Degraeuwe and Weiss, 2016) as demonstrated by the Volkswagen ‘dieselgate’ (US-EPA, 2015a, 2015b; FIA, 2017; Skeete, 2017). Second, emission factors can be derived from real-world on-road emission testing. On-road testing, referred to as the Real-Driving Emissions (RDE) test procedure, has recently been introduced in the European Union (EU) to complement laboratory tests for the type-approval of light-duty vehicles (European Commission, 2016). RDE tests use expensive type-approval PEMS equipment (Frey *et al.*, 2003; Kuranc, 2015), Africa lacks technical and financial resources; on-road emission measurements of the vehicle fleet are scarce to non-existent (Goyns, 2008). Only a limited number of studies have been conducted in the laboratory or on-road, in either case only gaseous emissions have been investigated:

- Lents *et al.*, (2005) explored the on-road measurement of exhaust gases in Kenya.
- Aduagba *et al.*, (2013) investigated idle mode testing for exhaust gases in Nigeria.
- Forbes and Labuschagne (2004) tested idle and accelerated modes and associated exhaust gases in South Africa.

Hence to date there has not been an estimate of the PM emission factors for vehicles in the African fleet during real-world driving conditions. Following Goyns (2008), we see a need to develop cost effective methods to determine the real-world gaseous and particulate emissions of vehicles in Africa.

The development of portable PM measurement equipment is particularly challenging. To date, the vast majority of real-world vehicle exhaust measurement systems are extremely costly (Miller *et al.*, 2007). Despite strict PM limits in the EU (European Commission, 2016), PEMS prototypes for on-road PM testing were only recently developed and evaluated (Mamakos *et al.*, 2013). The slow development and thus the lag in PM PEMS application may partly be explained by the complexity of the PM which alters state as exhaust conditions change making it difficult to measure (Mamakos *et al.*, 2013; Giechaskiel *et al.*, 2014). Gravimetric filter methods were applied to measure PM but this method is unsuitable for instantaneous PM measurements (Mamakos *et al.*, 2013); it lacks spatial resolution needed to characterize localized pollution hotspots.

Likewise, opacity measurements used for roadworthiness tests (Giechaskiel *et al.*, 2014) is unsuitable for deducting PM emission factors as only a poor correlation existed between opacity and PM concentration (Yanowitz *et al.*, 1999; Anyon P *et al.*, 2000; Bond *et al.*, 2004). In Africa, few countries have vehicle emission standards and regulations (UNEP, 2015), and those that do typically use opacity tests for in-use diesel vehicles to identify the most polluting vehicles (Walsh, 2014).

To address persisting knowledge shortfalls, we apply established methods for on-road emissions testing (Frey *et al.*, 2003; Zhang, 2006; Boroujeni and Christopher Frey, 2014; Kuranc, 2015) to evaluate a PM measurement emissions system on light-duty vehicles in Nairobi (Kenya). We deployed for the first time a low-cost multiplexed prototype parSYNC® sensor unit, referred to here as-parSYNC®-PEMS. The objective was to document the deployment of the prototype and critically assess the usability in obtaining variability in on-road PM emissions. A key hypothesis of this study is that synchronized on-road data collection using the three sensors of the parSYNC®-PEMS (namely ionization, scattering and opacity), allows an assessment of the different particle size ranges emitted from the vehicle exhaust. The real-world PM emissions described as a relative scale of multiple sensor voltage were related to driving pattern and vehicle operating conditions.

We expect that this study can be a proof of concept and demonstrate the collection, screening, processing and analysis of data from the three sensors of the parSYNC®-PEMS. The results can help to develop a protocol for the deployment of a rapid PM measurement system in a challenging urban environment.

2.2 Methodology

This study deployed a prototype parSYNC®-PEMS. Data from each test was collected, screened, processed and analyzed according to established protocols (Frey *et al.*, 2003; Zhang, 2006; Boroujeni and Christopher Frey, 2014; Kuranc, 2015),, with context-specific adjustments described in Sections 2.2.1-2.2.5.

2.2.1 Instrumentation

The prototype parSYNC®-PEMS used here is manufactured by 3DATX (3DATX, 2015). This instrument comprises of three sensors: ionization, opacity and light scattering. Individually each of these sensors gives a voltage reading for particles; the sensors combined signals give a voltage reading that has been shown in previous studies to be proportional to the magnitude of PM emissions (Ropkins *et al.*, 2016).Therefore, it is expected later development of parSYNC®-PEMS will give a combined PM reading from the sensor voltages. However, this development was beyond the scope of this study, thus sensor voltages were considered separately.

A wireless laptop was used to operate the equipment, graph the acquired data in real-time and save the voltage readings from the three sensors. The parSYNC®-PEMS (width = 22 cm, height = 27 cm, depth = 13 cm, weight = 2.6 kg) was installed in the boot of the vehicle; this typically took half an hour (see Figure 2.1).

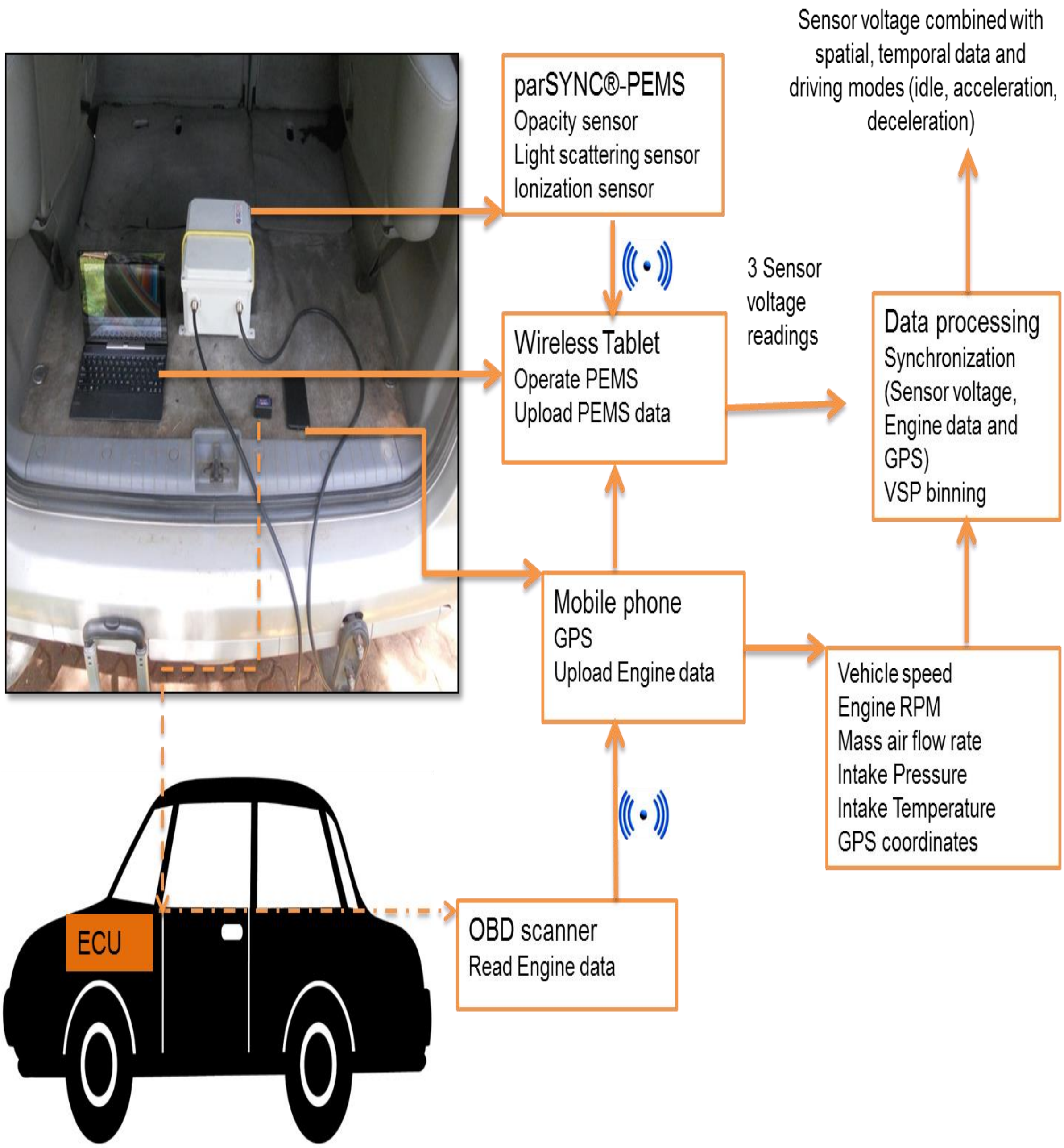


Figure 2-1: Stylized methodology layout for the installation of the parSYNC®- PEMS, the reading of engine data obtained through the ECU interface using the on-board diagnostic (OBD) scanner and the integration of the different data.

A sample of the exhaust was obtained using a Bureau of Automotive Repair (BAR) 97 sample probe. A low-cost generic Bluetooth engine scanner (ELM 327 mini) was connected to the OBD II interface to record the following engine parameters from the engine control unit (ECU): intake mass air flow rate, vehicle speed, engine rotation per minute (RPM), intake air temperature, and intake manifold pressure. We downloaded the TorquePro application from the Google play store to a smartphone to upload engine data from the OBD scanner at 1 Hz resolution. OruxMaps (version 5.0.2), an application from Google play store, was downloaded on a smart phone to acquire vehicle GPS coordinates, at 1 Hz. Before and after on-road data collection, the parSYNC®-PEMS was zeroed using ambient air to reduce drift.

2.2.2 Route choice and test conditions

The test route comprised a distance of 52 km and captured the typical driving conditions in Nairobi on urban roads, highways, and peri-urban roads (Figure 2.2). The vehicle load comprised the driver, a witness of the test and the test equipment, accounting together for some 170 kg. Tests were carried out in 2015 May at an average altitude of 1798 m, during moderate temperature conditions of 20-30 ^{o}C. The tests were conducted on tarmac (paved) roads outside of rush hours during work days and weekend between 10:00-15:00.

The vehicle operation was compatible with real-world consumer driving in Kenya. The urban part of the route comprised vehicle speeds of up to 50 km/h, including stop-and-go driving; the highway and rural parts were characterized by speeds between 50-100 km/h and 50-90 km/h, respectively. Vehicle specifications, driver identity, weather conditions, start time, end time, and each significant traffic event, including stops, were recorded for each trip in addition to the data described in Section 2.2.1.

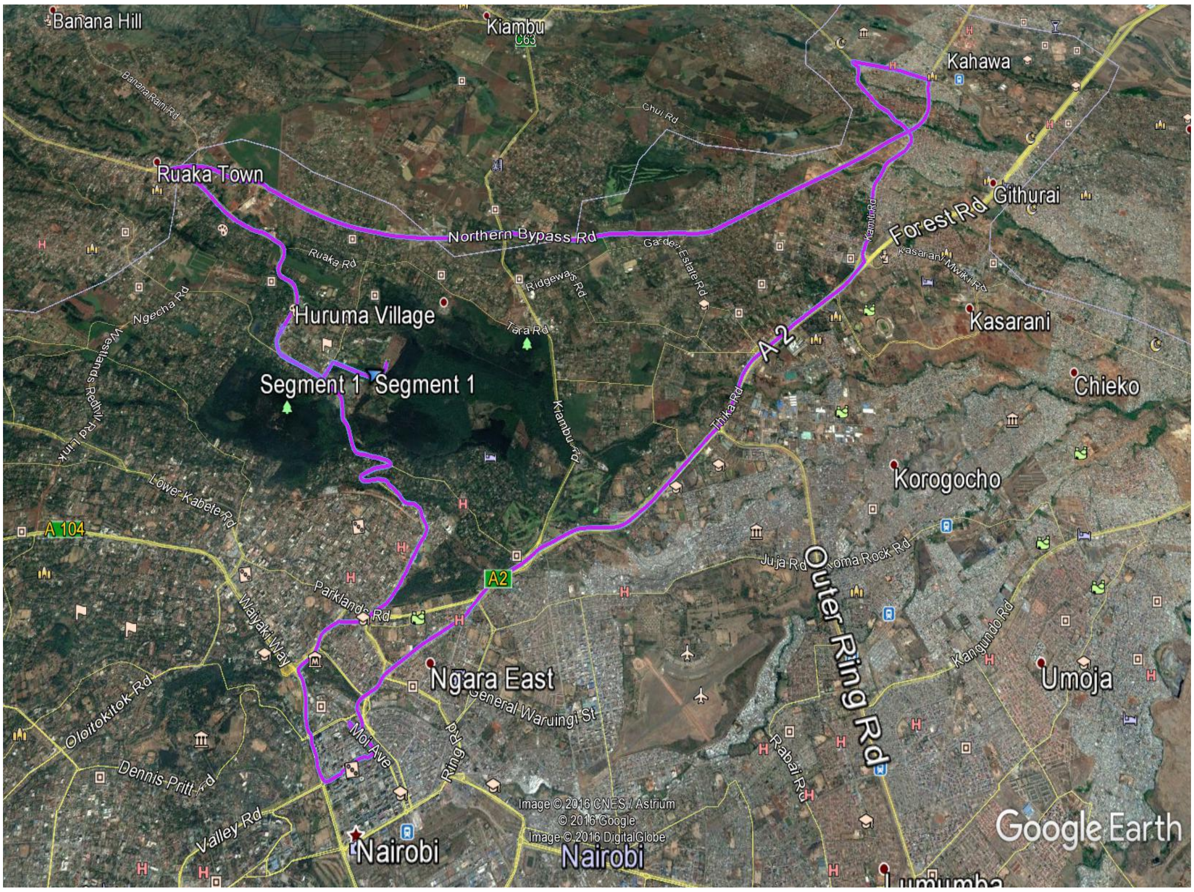


Figure 2-2: Test route in and around Nairobi (Kenya); Source: Google Earth

2.2.3 Vehicle selection, recruitment and operation

From a pool of vehicles, ten vehicles were selected that represented a range of attributes: fuel type, engine size, weight, utility, age, and technology. A test run was carried out to determine the viability of: (i) mounting the parSYNC®-PEMS unit and (ii) establishing engine interface with the vehicle-specific OBD scanner. Full listing of these tests is provided in, Table S1.

Two light-duty diesel vehicles with similar characteristics were selected for tests based on complete data from OBD, GPS and parSYNC®-PEMS). This resulted in four complete tests hereto labelled as Tests 8, 9, 10 and 11 (Table 2.1). These two vehicles were used to investigate the PM emissions and determine if it was possible to obtain meaningful sensor voltage readings. In addition, the turbocharge mode of the Mercedes Diesel was manually activated in Test 10 to investigate the response of the parSYNC®

sensors to a change in vehicle activity, keeping other variables such as route, driver constant.

Table 2-1: Vehicle specifications and summarised journey descriptions of Test 8, 9, 10 and 11. Odometer readings: *miles **km

	Test 8	**Test 9**	**Test 10**	**Test 11**
Diameter of exhaust (cm)	4.8	4.8	5.3	5.3
Fuel	Diesel	Diesel	Diesel	Diesel
Manufacturer	MITSUBISHI	MITSUBISHI	MERCEDES	MERCEDES
Model of vehicle	SHOGUN	SHOGUN	ML270 CDI	ML270 CDI
Transmission	AUTOMATIC	AUTOMATIC	MANUAL	MANUAL
Engine Size (cc)	3200	3200	2700	2700
Gross Value Weight (KG)	2255	2255	2870	2870
Fuel Tank Volume (L)	80	80	80	80
Year of Manufacture	2007	2007	2002	2002
Odometer reading (initial)	94117*	94150*	143045**	143100**
Odometer reading (Final)	94150*	94182*	143099**	143152**
Initial time	11:33	14:07	13:08	16:01
Final Time	13:18	15:39	14:59	18:22
Fuel top up (L)	Full tank	5.30	Full tank	6.31
Route	Predefined	Predefined	Predefined	Predefined
OBD scanner	YES	YES	YES	YES

Before the start of the test, vehicles were fueled to full capacity and the odometer reading recorded, at the end of the test vehicles were refueled to full capacity and odometer reading recorded again. This allowed estimating the fuel consumption of vehicles. For each test, complementary data were recorded including: driver’s name, number plate of vehicle, type of vehicle, diameter of exhaust, fuel type, manufacturer, model of vehicle, transmission, engine size, gross value weight (GVW), volume of fuel tank, year of manufacture, odometer reading (start/end of test ran) and the start/end time of the test. We abstained from preconditioning the vehicles. All measurements started with engine-on and include the cold-start phase.

For each test run, data from the three parSYNC® sensors were collected. The combined dataset for each test comprised: I) parSYNC® data with time stamps and 3 sensors voltage readings; II) Engine data with time stamps i.e. vehicle speed (m/s), GPS-longitude, latitude, altitude (m), engine RPM, intake air temperature (^{o}C), intake manifold pressure (kPa), torque (Nm), intake mass airflow rate (g/s) and III) Journey narrative i.e. driver details, vehicle specifications, weather conditions, journey details. Vehicle activity (speed, gradient, RPM, torque, intake manifold pressure and intake air flow rate) captured through the ECU interface, evaluated the relative importance of each driving mode to emissions change.

The test vehicle used in Tests 8 and 9 was a Mitsubishi Shogun; the vehicle used in Tests 10 and 11 was a Mercedes ML270 (Table 1). The Mitsubishi Shogun was manufactured in 2007, equipped with an automatic transmission and imported from the UK. The Mercedes ML270 was manufactured in 2002, equipped with a manual transmission an imported from Germany. In terms of Euro standards the Mercedes was equivalent to Euro III standards while the Mitsubishi was equivalent to Euro IV standards.

2.2.4 Data post-processing and analysis

The data post-processing (Figure 2.3) closely followed Frey *et al.*, (2003). In a first step, the collected datasets were combined and manually screened for errors, including indications that there was:

- Failure for Bluetooth connectivity between the parSYNC® unit and laptop, phone and OBD scanner.

- Disconnection between the tail-pipe and parSYNC© probe causing leakage during a test run.
- Failure of the GPS data to log to the phone.

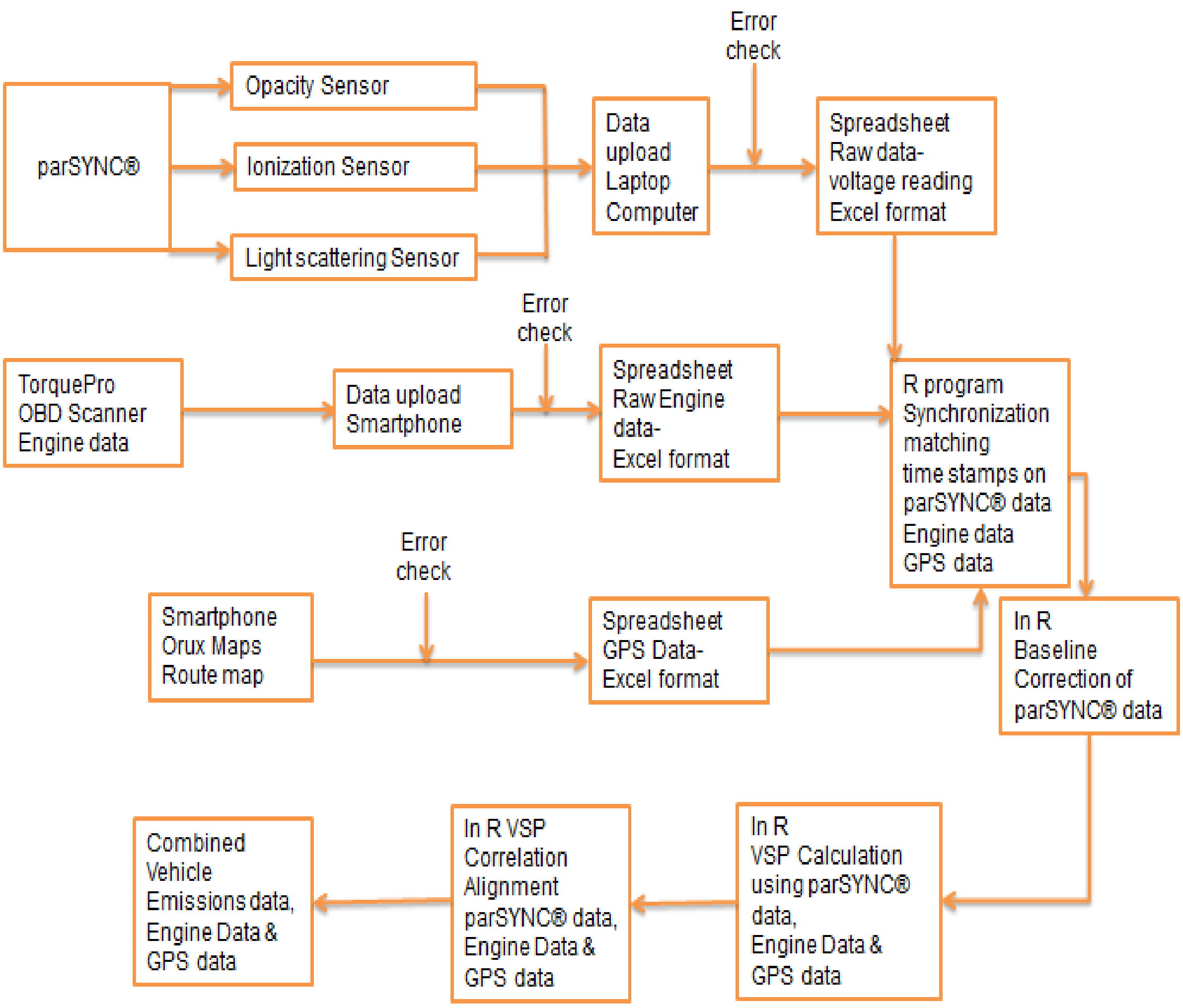


Figure 2-3: Collection, screening, processing of data obtained from the parSYNC®-PEMS, ECU and GPS.

The combined datasets of each test were converted to a tab-delimited format and stored in one folder. All data analysis and visualization, unless otherwise stated, was carried out using R (R core team, 2016).

Data synchronization

The individual datasets were imported into R and combined by timestamp to create a single dataset with the value of each variable at 1 second resolution using R package 'Stringi' (Gagolewski and Tartanus, 2016) and 'Lubridate' (Grolemund and Wickham, 2011). The voltage reading of the parSYNC® ionization and opacity sensors was then reversed as it was easier to work with PM events as peaks rather than troughs.

Baseline corrections

As the parSYNC®-PEMS was operated without an in-situ zero correction during this study, an offline correction was applied to the dataset generated by the parSYNC® sensors prior to the comparison with the engine data. The baseline correction was applied using a 'rolling ball' algorithm to the time aligned output voltage of the opacity, light scattering and ionization sensors, using the classic local window method (Kneen and Annegarn, 1996) and the R package 'baseline' (Liland and Mevik, 2015) to correct the non-zero flat line. The optimal baseline for each test were selected by visual inspection of the effect on the peaks of sensor voltage output by varying window length from 50 s to 1000 s (Liland *et al.*, 2011). A sample of the outcome of these baseline corrections are shown in Figure 2.5, showing the best fit selected through the variation of window length.

Vehicle specific power (VSP)

Vehicle fuel use and thus emissions depend on engine load, which has been quantified using vehicle specific power (VSP) (Jiménez-Palacios, 1999). VSP depends on vehicle speed, acceleration and road grade (Jiménez-Palacios, 1999; Zhang and Frey, 2005; Frey and Rouphail, 2008; Yao *et al.*, 2013; Boroujeni and Christopher Frey, 2014;

Rodríguez *et al.*, 2016). Assuming certain parameters are typical for light duty vehicles: m (mass of vehicle) = 1200 kg, A (vehicle frontal area) = 2 m^2, C_D (aerodynamic drag coefficient)= 0.3, VSP was calculated using Equation 1 (Zhang and Frey, 2005; Yao *et al.*, 2013; Rodríguez *et al.*, 2016). Vehicle speed and altitude were measured directly and used to determine road grade, velocity and acceleration, and combined to calculate VSP using Equation 2 (Boroujeni *et al.*, 2013; Boroujeni and Christopher Frey, 2014).

$$VSP = v\,[1.1\,a + 9.81 * grade(\%)] + 0.132] + 0.000302v^3 \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots.. Equation\ 1$$

v: velocity of vehicle (m/s)

a: acceleration of vehicle (m/s^2)

grade: vertical rise/slope length

To evaluate the sensitivity of the parSYNC® sensor voltage to VSP, values of VSP at each time step were categorized into 19 bins, bins 0-10 represented acceleration, bin 11 for idling, bin 12-19 for decelerations/breaking, following the model presented previously (Lents *et al.*, 2005; Rodríguez *et al.*, 2016). Relating the driving mode (idle, acceleration, deceleration) to VSP, the real-world relationship between driving patterns and vehicle emissions was established (Rodríguez *et al.*, 2016).

Alignment of sensor voltage with VSP

Further synchronization of data took into consideration that there is a time lag between changes in engine parameters, the composition of the exhaust at the tailpipe, and the response of the parSYNC® sensor voltage Because the time difference between events such as the rise in RPM, increase in speed, or acceleration should coincide with the increase in pollution concentration (Sandhu and Frey, 2013), alignment was applied on the peaks of sensor voltages and these rises, using the ‘pems.utils’ R package (Ropkins, 2016). Here, the alignment used adjusted the time of the sensor voltage reading to maximize the correlation between sensor voltage reading, and VSP.

2.3 Results

The initial recruitment of 10 vehicles resulted in 15 tests, summarized in Table S1. For Tests 8, 9, 10 and 11, we had collected a complete data set from the parSYNC®-PEMS, the OBD scanner and the GPS. These test results were therefore further analyzed and the results of these tests are presented here.

2.3.1 Real-world activity data

For all tests, speed, altitude, RPM and torque were similar as shown in Figure 2.4, although Test 10 had a slight variation on the chosen route. The test durations and average speeds range between 94 min for Test 8 and 9, 110 min for Test 10 and 139 min for Test 11. Approximately 40% to 60% of the test distance was driven at vehicle speeds of less than 5 m/s; the maximum speed peaked at 30 m/s; idling accounted for approximately 43% of the test duration. The vehicle speed is non-normally distributed and positively skewed. Some 46% (with a deviation of 4%) of the test distance was driven at an altitude of 1650-1700 m. Engine RPM between 1500-1000 accounted for some 46% to 48% 69% of the test duration. Engine torque of less than 200 Nm was observed for 53% to 64% of test time. Speed, altitude, RPM and torque for all test runs followed a similar pattern of distribution. Intake manifold pressure and intake mass air flow rate for Test 8, 9, and 11 followed a similar distribution with the highest frequencies of: (i) 77% to 99% of intake manifold pressure at 80-100 kpa, (ii) highest distribution 34% to 49% of intake mass air flow rate at less than 20 g/s. However, for Test 10 intake manifold pressure and intake mass air flow rate distribution was different from other test runs, the highest frequency of 81% of intake manifold pressure was between 20-40 kPa, while the highest frequency of intake mass air flow rate (58%) was between 280-340 g/s.

Thus the mean intake manifold pressure for Test 10 decreased by an order of magnitude ~4 (21.5± 0.03 kPa) and increased by the same for intake mass air flow rate (234.9 ±1.33 g/s) when compared to the other test runs.

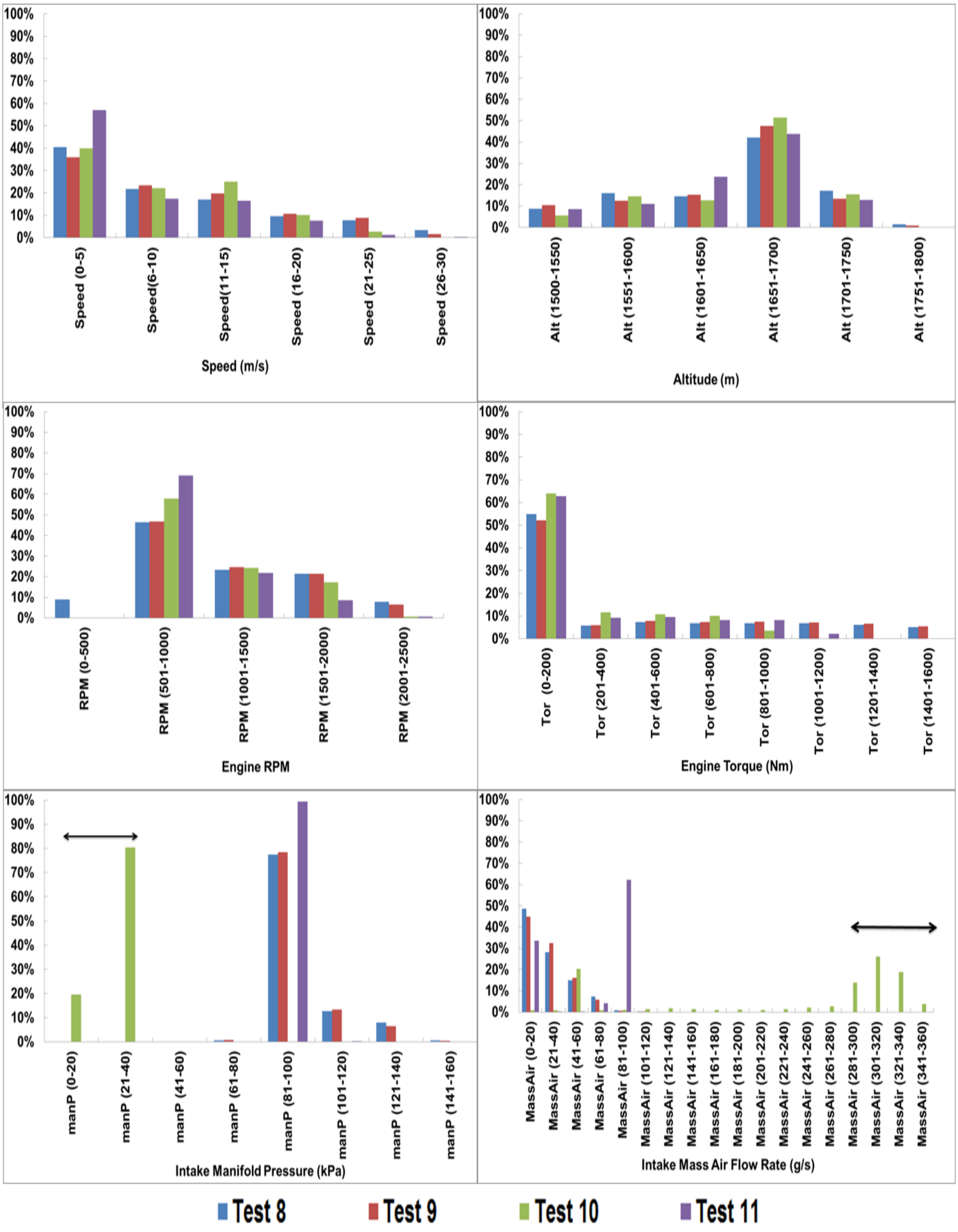
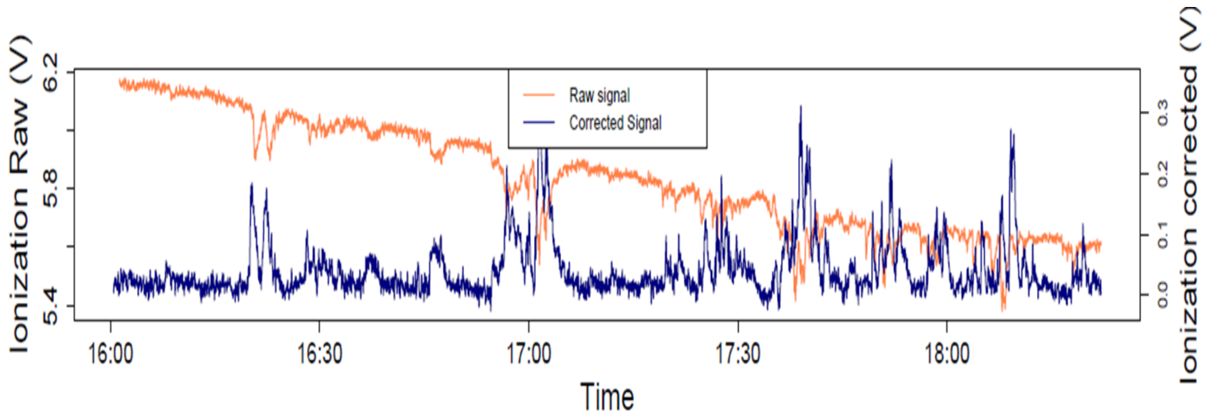


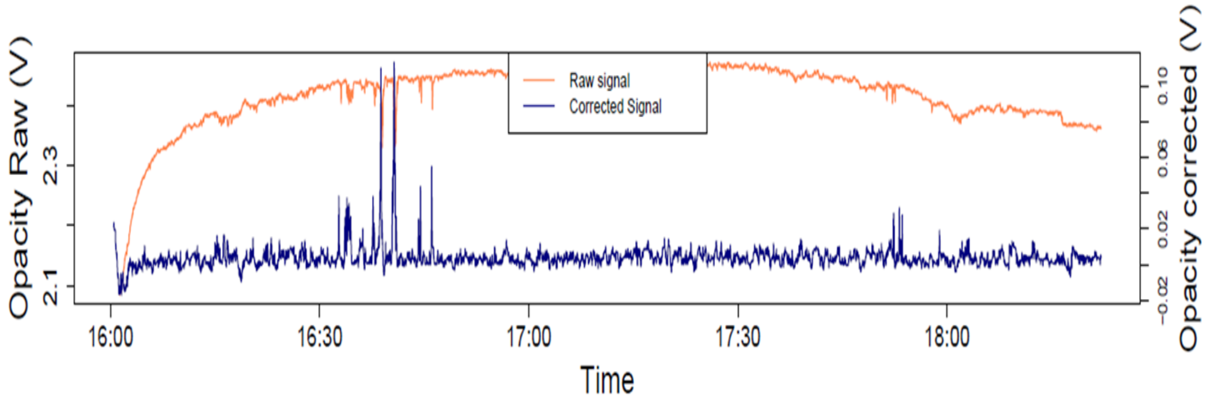
Figure 2-4: Frequency distribution of vehicle speed, altitude, RPM, engine torque, intake

manifold pressure and intake mass air flow rate of Tests 8, 9, 10, and 11.

2.3.2 Data alignment and baseline corrections

The raw output from the scattering, ionization and opacity sensors for Test 11 (Mitsubishi Shogun) is shown as an example in Figure 2.5, alongside the baseline corrected voltage signals. Visual inspection of the voltage signals shows a similar pattern of peaks in the scattering and ionization sensors, where 15 distinct peaks are identifiable. However, the opacity sensor shows a different pattern with less than 5 distinct peaks identifiable. Corresponding figures for the other three tests are shown in Figure S7-S10. A similar pattern of distinct peaks was observed in Test 8, in all three sensors at 12:09, 12:26 and 12:52, Test 9, at 14:25 15:12. For Test 8 and 9 these peaks were at nearly identical place in the journey, at 82 minutes and 64 minutes. The sensor voltage from Test 10 had numerous peaks and troughs (>20), here scattering and opacity had a similar pattern of distinct peaks.





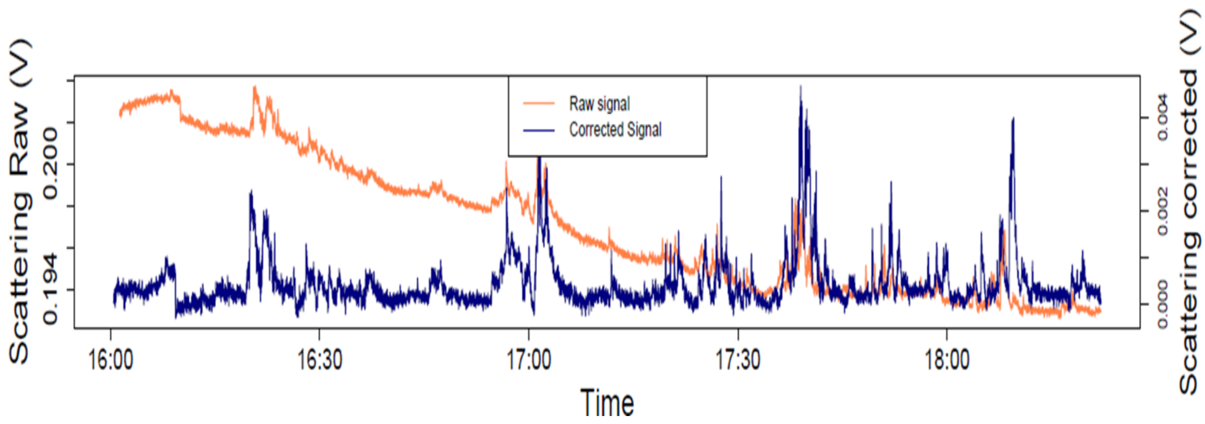


Figure 2-5: Plot of uncorrected data (raw signal in orange) from Test 11 and baseline corrected data (corrected signal in blue) of the opacity, light scattering, and ionization sensors of the parSYNC®-PEMS.

2.3.3 Spatial map of sensor voltage

An example of the variation in the sensor voltage output, time traces and vehicle position and sensor voltage is shown in Figure 2.5 for Test 11. The spatial and temporal map shows how a measured value, ionization sensor voltage in this case, correlates with time and position of the moving vehicle.

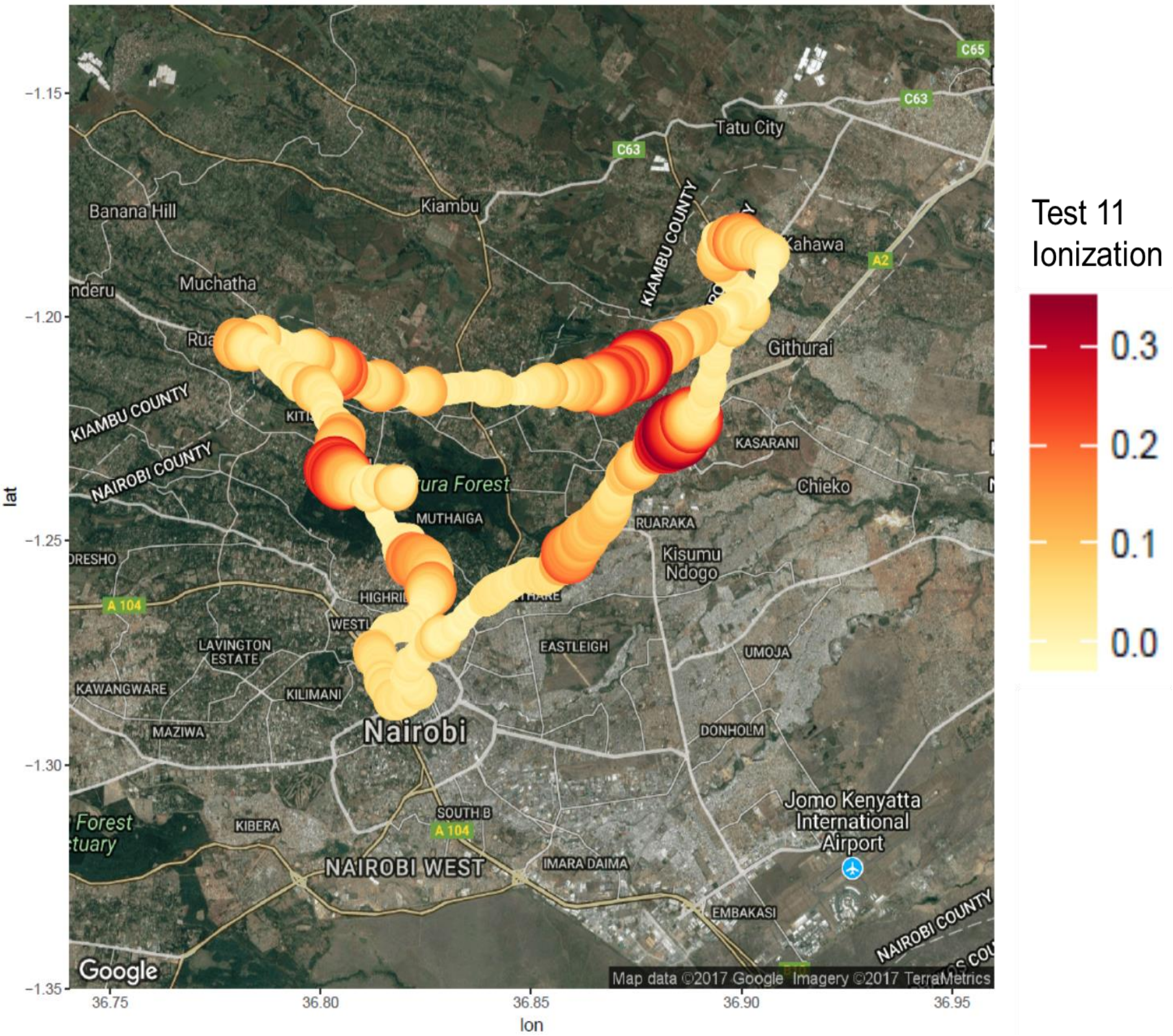


Figure 2-6: Voltage of the ionization sensor from the parSYNC®-PEMS in Test 11 conducted with the Mitsubishi Shogun, superimposed on the route map (map data ©2017 Google); plot established by using R package ggmap , ggplot2 and openair (Carslaw and Ropkins, 2012; Kahle and Wickham, 2013; Carslaw, 2015).

Most voltage peaks (red color on the map in Figure 2.6) tended to coincide with acceleration events (for the other tests see Figure S51 to Figure S62). There were incidences of high spike in voltage, for example in Test 8 and 9 that occured at 12:52 and 15:12, this coincided with a diversion on the road (noted on the journey narative), so the test vehicle was momentarily on a unpaved road from a tarmacked road. However, this same spikes are not apparent in Test 10 and Test 11, instead there are a series of peaks and troughs.

2.3.4 Data alignment and baseline correction

The raw output from the scattering, ionization and opacity sensors for Test 11 (Mitsubishi Shogun) is shown as an example in Figure 2.6, alongside the baseline corrected voltage signals. Corresponding figures for the other three tests are shown in supplementary section Figure S7-S10. Visual inspection of the voltage signals shows a similar pattern of peaks in the scattering and ionization sensors. However, the opacity sensor shows a different pattern. A similar pattern was observed in Test 8, in all three sensors at 12:50 and Test 9, at 15:10. For Test 8 and 9 these peaks were at nearly identical place in the journey, at 77 minutes and 60 minutes.

2.3.5 Multiplex correlation of the sensors

A best linear regression of the three sensor voltage output in pairs (scattering/ionization, scattering/opacity, ionization/opacity) was examined and the visualization of the three sensor relationship (ionization, opacity, scattering) plotted. An example plot of Test 11 is presented in Figure 2.7. A visual inspection of the 3D plots from Test 8, 9, 10 and 11 found Test 10 to be the best fit as there was a close correspondence in the voltage output of the three sensors.

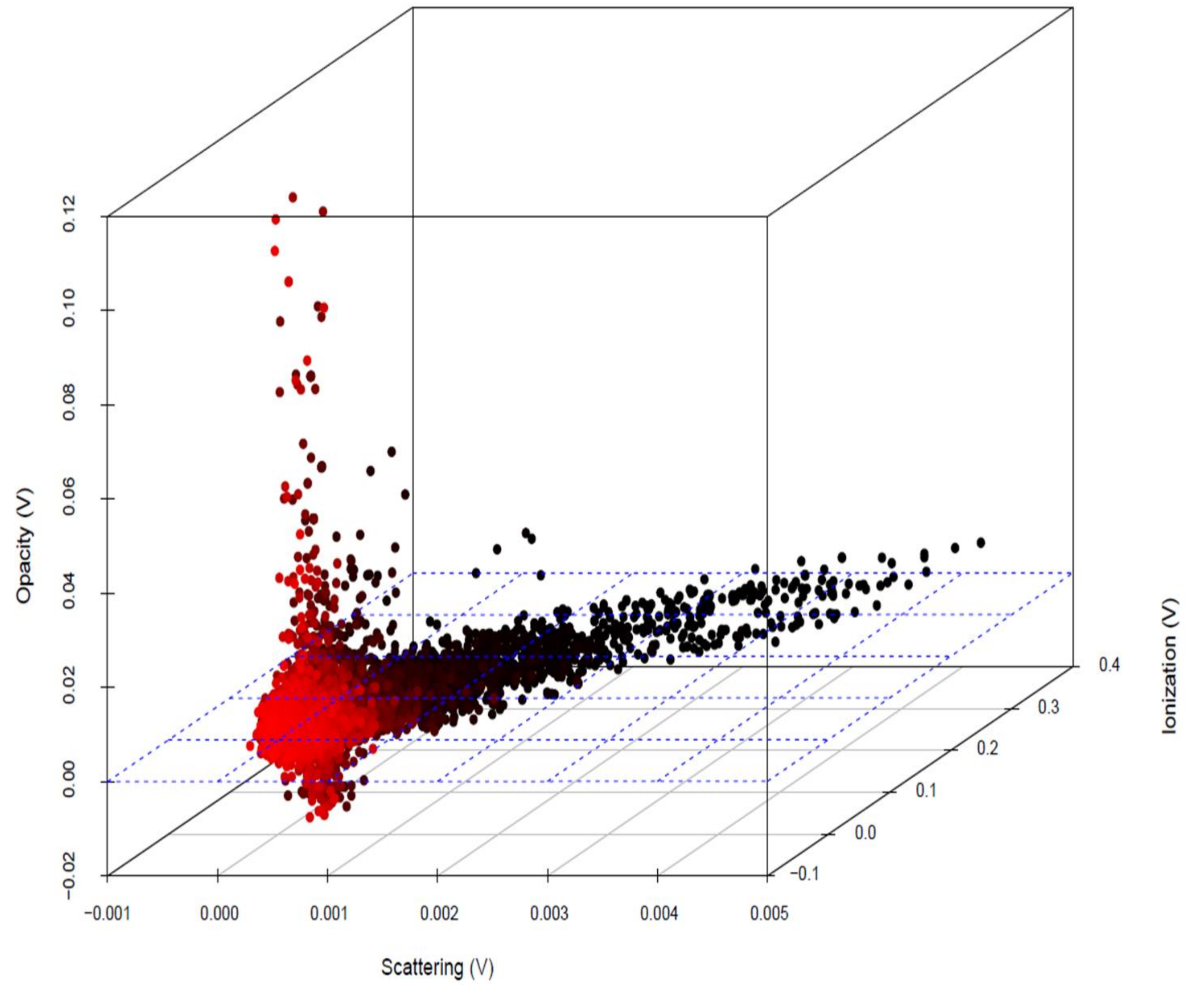


Figure 2-7: Scatter plot (3D) sensor voltage of Test 11, three sensors (opacity, light scattering ionization) from the parSYNC®-PEMS. A linear regression line of three sensors is shown as the blue grid. The color pallet represents sensor voltage relation to the y-coordinate (ionization voltage).

A statistically significant relationship between opacity, scattering and ionization sensor voltage was found in Test 8, 9, 10 and 11 with $P< 0.001$, this is presented in Table 2.2. Test 10 and Test 11 had a strong correlation between ionization, opacity and scattering sensor voltage with $R^2 = 0.93$ for Test 10 and $R^2 = 0.76$ for Test 11, while Test 8 and 9 had a weaker correlation between the sensors with Test 8, $R^2 = 0.23$) and even less with Test 9, $R^2 = 0.08$.

Table 2-2: Table of statistics parameters of the relationship between the sensors voltage (ionization, opacity, scattering) of the test runs (Test 8, Test 9, Test 10, Test 11).

Test	Parameter	Scattering/ Ionization	Scattering/ Opacity	Ionization/ Opacity	3 Sensors interaction
Test 8	Equation	$Y_1 = 3.34*10^{-3}X_1 + 5.59*10^{-5}$	$Y_1 = 0.13*10^{-3}X_1 - 2.0*10^{-4}$	$Y_1=12.67X_1 + 0.30$	$Y_1 = 1.10*10^{-1}X_1 + 2.20*10^{-3}X_2 - 4.50*10^{-4}$ Y1:scattering X1: opacity X2: ionization
	R^2	0.23	0.31	0.4	0.4
	P value	P<0.001	P<0.001	P<0.001	P<0.001
Test 9	Equation	$Y_1 = 1.60*10^{-4}X_1 + 1.90*10^{-4}$	$Y_1 = -2.50*10^{-3}X_1 + 2.27*10^{-4}$	$Y_1 = 0.22X_1 + 0.07$	$Y_1 = 1.65*10^{-4}X_1 - 2.54*10^{-3}X_2 + 2.16*10^{-4}$ Y1:scattering X1: ionization X2: Opacity
	R^2	0.03	0.05	$4.0*10^{-4}$	0.08
	P value	P<0.001	P<0.001	P = 0.14	P<0.001
Test 10	Equation	$Y_1=8.08*10^{-2}X_1 + 9.53^{*}10^{-3}$	$Y_1=0.40X_1 + 1.00*10^{-3}$	$Y_1=1.20X_1 + 0.39$	$Y_1 = 1.27*10^{-2}X_1 + 2.27X_2 + 1.93*10^{-3}$ Y1:Opacity X1: ionization X2: Scattering
	R^2	0.22	0.93	0.23	0.93
	P value	P<0.001	P<0.001	P<0.001	P<0.001
Test 11	Equation	$Y_1 = 6.13*10^{-3}X_1 + 4.16*10^{-4}$	$Y_1 = 6.13*10^{-3}X_1 + 4.16*10^{-4}$	$Y_1 = 0.63X_1 + 3.85*10^{-2}$	$Y_1 = 1.04*10^{-2}X_1 - 3.96*10^{-4}X_2 + 1.73*10^{-5}$ Y1:scattering X1: ionization X2: Opacity
	R^2	0.76	$6.19*10^{-3}$	$9.23*10^{-3}$	0.76
	P value	P<0.001	P<0.001	P<0.001	P<0.001

2.3.6 Relationship between vehicle activity and sensor output

Despite the significant uncertainties obtained from the calculations of the voltage means, in general, there was an increase between VSP bins 12 -18 for all sensors voltages and a decrease between VSP bins 0-10. These VSP bin results can be viewed in detail in the supplementary section of the paper. Figure 2.8 shows acceleration mode was highest in Test 8 all sensors, Test 9 (ionization, opacity), Test 11 (ionization, scattering). Test 10 all sensors, deceleration was highest, followed by idle and then acceleration. Test 10 as shown in Figure 2.8, was observed for example to have a magnitude of 13, 33, and 121 times the sensor voltage for ionization, opacity and scattering respectively when compared to the means of the other test runs, for example in Test 11. It was also observed that when the engine parameters were compared to the other test runs, the intake air flow rate of Test 10 quadrupled while intake manifold pressure reduced by a quarter over the same period. This was due to the driver of the vehicle engaging the vehicle's manual turbocharge system within the first ~20 minutes of the journey and for the remainder of the journey.

A welch's t-test comparing the average voltages from the different sensors for acceleration, idle and deceleration found them to be statistically significantly different from each other. Out of the 36 pairwise tests representing 4 test runs, and three sensor voltage, 75% are statistically significant means from each other, one pairwise test from Test 9 comparing idle mode and deceleration of the scattering sensor is borderline ($p = 0.05$). It should be noted that in examining all the insignificant cases, the 95% confidence interval which indicates the likelihood the means of the compared modes would fall between certain intervals, the lower end was always a negative voltage. 96% of pairwise (idle-to-acceleration) and (deceleration-to-idle) mode was statistically significant, hence the majority of the statistically insignificant cases occurred with the pairwise acceleration-to-deceleration cases.

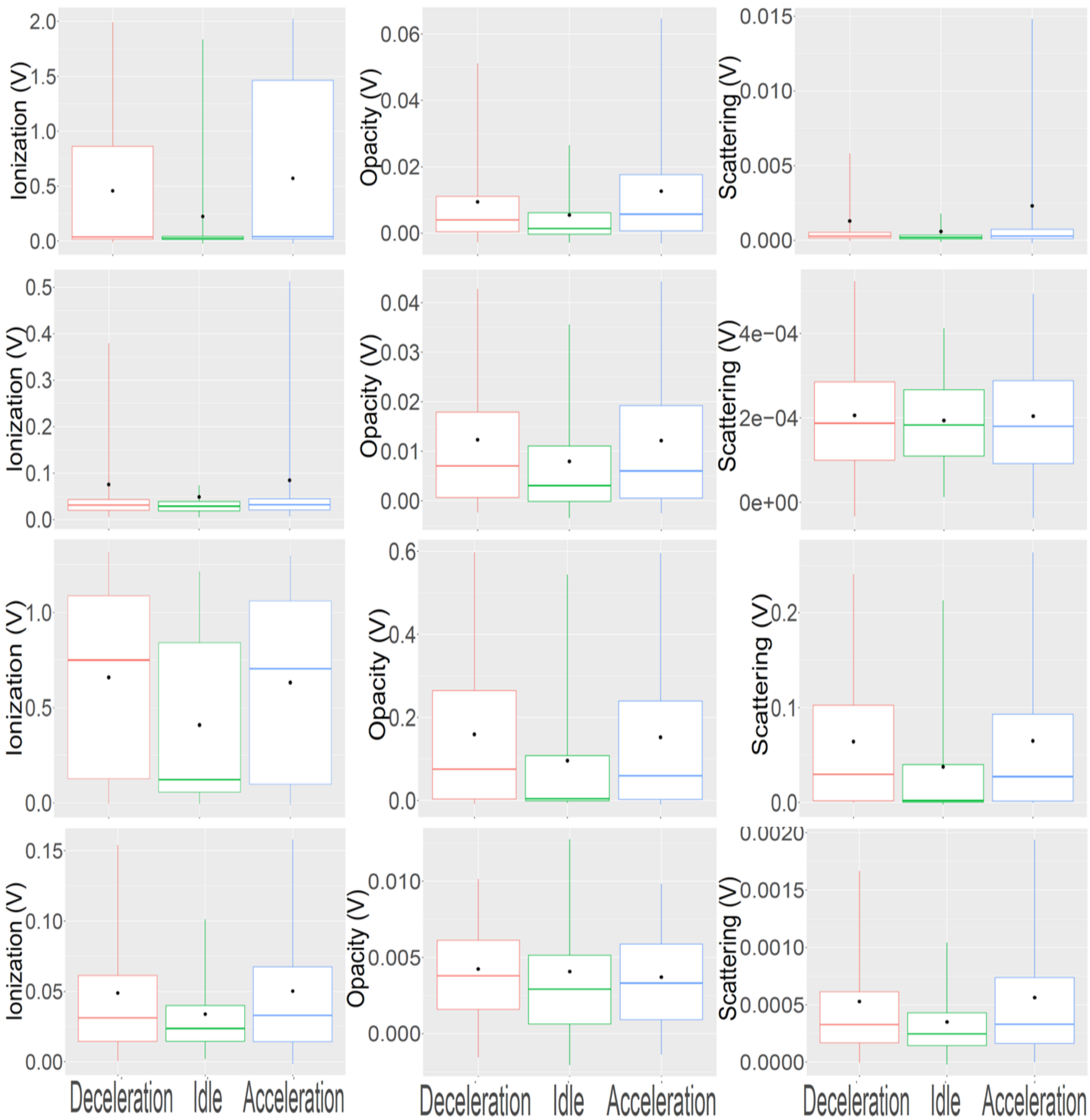


Figure 2-8: A panel of boxplots with different driving modes (deceleration, idle and acceleration) for ionization, opacity and opacity sensor voltage for Test 8 (at the top of the panel) Test 9 (2nd from the top), Test 10 (3rd from the top), Test 11 (bottom of the panel). The box and whisker plot represents the central 50% of the data (median). The lower edge of the box plot is the first 25th percentile and the upper edge of the box plot is the 75th percentile. The black dots represent the mean.

2.4 Discussion

This paper describes a protocol for the deployment and analysis of data retrieved from a parSYNC®-PEMS prototype in Nairobi (Kenya) in the critical evaluation of a novel emission measurement system. In the context of conducting real world emission testing in Nairobi, as compared to a North American or European city, there are two challenges that increase the difficulty of obtaining reliable estimates of real world emissions. The first are environmental or practical challenges, and include the condition of the roads (potholes, unpaved roads etc.), traffic congestion, lack of immediate technical support and a lack of data to characterize each vehicle comprehensively. The second set of challenges relate to the ability to characterize emissions across a representative set of vehicles, which is made more difficult in Nairobi through a lack of vehicle emission standards, unreliable I/M of vehicles, unreliable and variable fuel quality, and the age of vehicles. This analysis details the experimental procedure that was used to overcome these challenges using data from two vehicles over four test runs. Although these tests are preliminary this could, in the future, be used to undertake a more comprehensive analysis of a larger number of vehicles in Nairobi and other African cities. This will aid in the cost effective implementation of a more robust inspection and maintenance program, in the development of PM emission factors and characterization of real world emissions in this region. However, additional evaluation of the parSYNC®-PEMS is necessary since the protocol did not include calibration with a reference instrument.

It has been demonstrated previously that real-world gaseous measurements are up to 10 times more during the acceleration compared to idle mode (Frey *et al.*, 2003). It has also been shown that VSP bins with acceleration mode contribute the most to total gaseous and particulate real-world emissions (Frey *et al.*, 2003; Huang *et al.*, 2013; Zheng *et al.*, 2015; Choudhary and Gokhale, 2016; Rodríguez *et al.*, 2016). Test 8, 9 and 11 as shown in Figure 2.8, show a similar result, with acceleration mode (when paired with idle and deceleration), having a higher sensor voltage 75% of the time, for the ionization, opacity and scattering sensors. A previous study has shown stronger dependence of PM emissions to VSP in light duty petrol cars compared to diesel cars, where particle number emissions increased by a magnitude of 3 from idling to highest VSP (Huang *et al.*, 2013). Measured in the aforementioned study was a light duty diesel, Euro 3 emission standard vehicle manufactured in 2010 with 1.9 L engine, therefore smaller, newer and better technology than this study's test vehicles. But even with these differences, similar to present study, PM emissions rate for diesel vehicle was found to peak in the highest VSP and speed bin greater than that at idling (Huang *et al.*, 2013).

Various studies have confirmed VSP as an appropriate metric to obtain correlations between driving patterns and vehicle emissions: gaseous pollutants and black carbon (Frey *et al.*, 2003; Zhang, 2006; Carslaw *et al.*, 2013; Ježek *et al.*, 2015; Zheng *et al.*, 2015; Rodríguez *et al.*, 2016). The VSP profile for the vehicles tested in Nairobi showed a similar profile to vehicles tested in Bogota, 91-94% of the time vehicles tested in Test 8-11 operated in a VSP between -15.2 and 17.7 kW ton $^{-1}$, while in Bogota 95% of the time vehicles tested operated in the same range (Rodríguez *et al.*, 2016). Such VSP values in Nairobi reflect real-world driving conditions in the city on an urban road such as downtown Nairobi, highways such as Thika highway, and peri-urban road such as Gigiri road, which were part of the selected test route. These conditions, similar to those like in Bogota, are characterized by heavy traffic congestion with stop-and-go, low speeds, many stops and idling (Rodríguez *et al.*, 2016). Furthermore, European derived driving cycle have been shown to be poor representation of typical driving patterns in urban areas in Africa due to high proportion of idling, different driving styles and atmospheric conditions (temperature, humidity, altitude) (Goyns, 2008). In this study, Nairobi VSP profile was found to be similar to Bogota's and a better fit than the European driving cycle.

Previous studies have demonstrated that turbocharging in diesel vehicles under higher engine loads could double NO_X to CO_2 emissions ratio for newer model cars compared to old ones (Carslaw *et al.*, 2011). This could explain the increase in the sensor voltage for Test 10, compared to the other tests as turbocharge of the engine was manually engaged. It was also most likely the reason why Test 10 showed a reversal in pattern from other tests as acceleration mode in this test was not the highest sensor voltage.

Given the principal of operation for turbocharge engines, where engine power output is increased through increased compressed air flow (North, 2007), applying ideal gas law, the pressure and volume change for Test 10 was accounted for. The decrease in sensor voltage for acceleration mode, in Test 10 with maximum power load would also be accounted for by the increased air flow rate. Therefore whilst turbocharging has decreased CO_2 emissions, and increased NO_X emissions, additional evaluation is needed on the effects of turbocharging on PM emissions. Especially in the aftermath of dieselgate where the vehicles tested and found to exceed NO_X emissions by a factor of 15 to 35, were turbocharged light duty passenger vehicles (Thompson *et al.*, 2014), these were similar in weight and engine size to those tested in Kenya. Although the vehicles tested in Kenya are older, fuel quality is poorer than those tested in USA, these fleets from developed countries will most likely be imported to developing markets regions in Africa in the future.

A multiplex instrument using three sensors is novel as is the study of the correlation of the three sensors for PM measurement. There are real-world PM studies that have assessed the correlation of these sensors to PM but only using sensors deployed separately, i.e. opacity tests (Anyon P *et al.*, 2000; Giechaskiel *et al.*, 2014), and light scattering tests (Anyon P *et al.*, 2000; Miller *et al.*, 2007; Khan *et al.*, 2012; Giechaskiel *et al.*, 2014). Light scattering had a high correlation between reference instruments (R^2 =0.92), while opacity had low correlation (R^2=0.12), so opacity was found to be a poor surrogate for fine particulate matter (Anyon P *et al.*, 2000). In this study a correlation between the three sensors, ionization, opacity and scattering sensor output voltage was explored. Correlation was highest (R^2= 0.93), in Test 10, which also was found to exhibit the highest individual voltages of all three sensors (see Table 2.2). Viewing the statistics parameters in Table 2.2, it was concluded that the voltage relation between all three sensors was best for the older vehicle (Mercedes Benz) vehicle. In a previous study, best data correlations were achieved when correction factors were applied to account for the ultrafine particles undetected by the scattering sensors and to correct for humidity (Miller *et al.*, 2007). The three sensors in the parSYNC®-PEMS detect different particle ranges from the exhaust, as opacity is reported to have a detection limit of up to 15 mg/km while light scattering detection limit 0.5 mg/km (Giechaskiel *et al.*, 2014), whilst the ionization sensor detects the ultrafine particles. Petrol cars and diesel vehicle exhaust particles mainly correspond to nucleation-mode and accumulation mode respectively (Huang *et al.*, 2013). Therefore, since the best voltage relation between sensors was from the older vehicle, and the test vehicles were diesel then the parSYNC®-PEMS performed best for the accumulation mode. Thus the combined parSYNC®-PEMS voltage when calibrated will at the very least give an instantaneous second-by-second PM concentration and at most on-road PM particle and size composition changes. In this study, the parSYNC®-PEMS prototype was kindly released by the manufacturer to accommodate our research desire and due to time and budget constraints calibration was not possible with a reference instrument.

The OBD ports and scanners were difficult to work with, Alessandrini *et al.*, (2012) reported on the rarity of acquiring engine parameters such as intake air flow and air to fuel ratio. Rule of thumb on OBD scanners has been for European and Asian vehicle imports to use ISO 9141 supported protocol scanners while GM and ford use SAE J1850 supported protocol scanners (Lee *et al.*, 2011). Vehicles in Kenya are often reconditioned second-hand imports from Japan (ERC, 2015b), so even though the OBD scanner used was ISO 9141, Test 1-7 and Test 11-14 were not successful in obtaining engine data from the ECU. In fact this particular scanner only worked on the vehicles imported directly from Europe (Test 8, 9, 10 and 11) or in Test 15, USA, even though Test 8 and 9 vehicle was of Japanese make. The scanner did not work on vehicles of Japanese make imported from Japan to Kenya. This was unexpected as all vehicles post year 2000 are meant to be OBD II compliant (Alessandrini *et al.*, 2012; Kuranc, 2015). A similar make of the OBD scanner was successfully used to in Korea for what is presumably a Korean passenger vehicle (Baek and Jang, 2015). So even though OBD data loggers have made collection of real-world vehicle activity viable, more investigation ought to be carried out on how accessible these data is especially in developing countries fleets.

In processing the data from the parSYNC® sensor array, the ‘rolling ball’ baseline corrections were applied as shown in Figure 2.5. ‘Rolling ball’ baseline corrections have been applied before on spectra peaks to identify and correct baseline by using visual inspection and statistical analysis to select best fit (Liland *et al.*, 2011). In the present study, the window in the baseline correction best fit was window length 250 for all tests and all sensors except opacity, and then best fit was window length 50. In general, the baseline corrections were robust except for when sensor voltage readings suddenly shifted, examples of which can be seen for all sensors, in Test 11 for example at a peak at 17:00 for both scattering and ionization sensor. A similar pattern was noticeably observed in Test 8, in all three sensors at 12:52 and Test 9, at 15:12. For Test 11, this pattern was observed in scattering sensor and ionization sesor at 18:08. In Test 8 and 9, 11 this coincided with a diversion on the road (noted on the journey narrative), so the test vehicle was momentarily on a dirt road from a tarmacked road. Surprisingly, no sudden shifts were detected in Test 10. Such sudden shifts called ‘artefact jumps’, have been noted in other instrumentation (for ambient PM measurement) due to incorrect instrument offset or factory calibration being in-adequate for these PM concentrations (Rivas *et al.*, 2017). It was recommended in Rivas et al (2017) to handle PM data with care and to automate zeroing of the instrument. In baseline correction, a potential challenge arising from applying the incorrect algorithm, is the baseline cuts above the lower parts of the peaks (Liland *et al.*, 2011). In this study, this happens in places with the sudden jumps where the baseline cuts the base of the peak resulting in negative voltage values, in Test 8, at 12:52, Test 9 at 15:12. However due to the aggressive drift noted, and limited number of tests, we did not obtain an optimal algorithm. Further tests will need to be conducted for an optimal algorithm for baseline correction.

A PEMS should respond instantaneously to input changes otherwise given the high temporal resolution of measurements, this could introduce error and uncertainty (Zhang, 2006). In reality it does not because of the time the exhaust takes to travel from the engine to the detection by the instrument. In this study, we adjusted for the lag by visually inspecting the time stamp and synchronizing the different data streams. In a previous study, laboratory tests and numerical simulations were used to quantify response times and rectify its effect on emissions (Zhang, 2006). Using gas PEMS, response time was found to vary to up to 10 s and the difference between measurements not corrected for different response times could be as large as a 2.5 times (Zhang, 2006). OBD data loggers were also found to have a time drift of up to 3 seconds (Goyns, 2008), the time lag in this case was corrected for manually by visually comparing OBD engine speed and GPS speed profiles and adding a correction factor. In this study, there were uncertainties introduced due to the correlation lag detected on the different sensors. The aim of the synchronization and correlation alignment (explained in 2.2.4) was to adjust the voltage readings for the time lag between changes in engine data and changes in the composition of the exhaust. An example of the correlation alignment for Test 11 is shown in Figure 2.9. The correlation was based on the calculated VSP and sensor voltage for scattering, ionization and opacity sensors. The lag adjustment of VSP for the ionization sensor was (-36), opacity (-27), scattering (-33). Hence the optimum adjustments suggested for each of the three sensors were different, and for all three sensors there were multiple adjustments that had very similar improvements in alignment. Given these discrepancies, the remaining results were not correlation aligned, even though visual inspection synchronization was initially applied to the data set. Improper synchronization between VSP and modal emissions rates have been shown to decrease variability between the lowest and highest average modal emission rate (Sandhu and Frey, 2013), this may explain the 25% of the time (see Figure 2.8), when the mean parSYNC® sensor voltage between different modes was found to be statistically insignificant .Further work is needed to identify the optimum adjustment of the parSYNC® PEMS voltage output to account for this time lag.

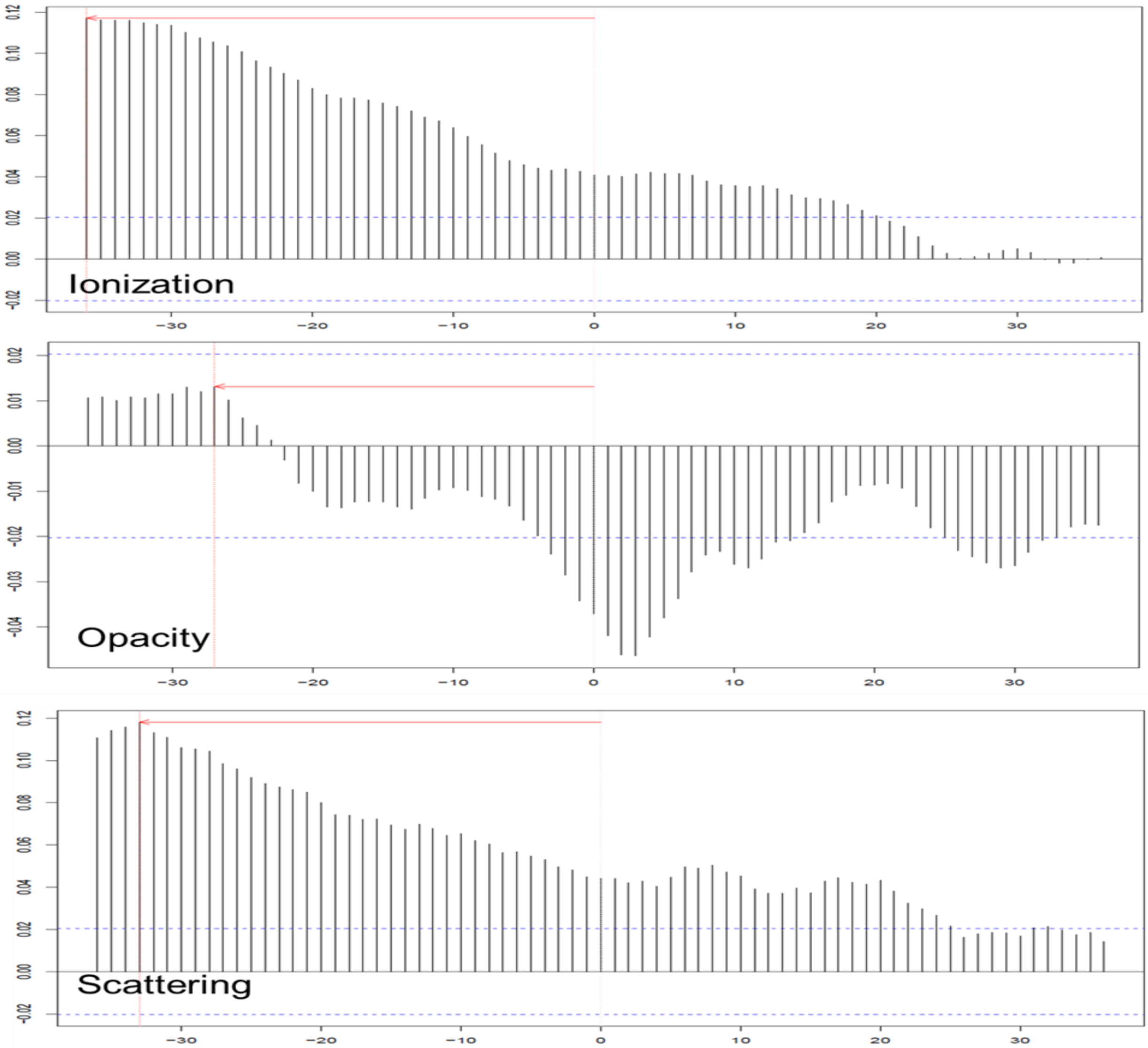


Figure 2-9: An example plot of correlation alignment using pems.utils with VSP from engine data and sensor voltage from (ionization, opacity and scattering) for Test 11 from parSYNC®-PEMS.

Advancement of vehicle emission reduction technology can yield up to a 95% reduction of PM from the exhaust of the vehicle (Chambliss *et al.*, 2013; Mamakos *et al.*, 2014). Particle filters are not present in most vehicles used in Africa as these fleets comprise of old vehicles and second-hand imports (Doumbia *et al.*, 2012; Liousse *et al.*, 2014; Marais and Wiedinmyer, 2016). Furthermore, lack of inspection and maintenance (I/M) programs would render these emission reduction technologies ineffective (Pillot *et al.*, 2014), in addition poor fuel quality also restricts the effectiveness of these measures. The roads in African cities is often inadequate and in poor condition; few paved roads mostly in poor condition and the rest of the roads are unpaved (Kumar and Barrett, 2008; Olvera *et al.*, 2013; UN-Habitat, 2013). The test vehicles' age and technology have a similar profile of vehicle fleet in Nairobi according to a recent survey which found average age of this vehicle class i.e. passenger cars to be 11.1±0.57 years (Mbandi *et al*., in preparation). These passenger cars, classified as AfritypeM1D (engine size >2000 cc), were also shown in this study to have the poorest fuel economy among the passenger cars.

2.5 Conclusion

The critical evaluation of the protocol and deployment of parSYNC®-PEMS yields robust real-world PM emissions data presented as multiple sensor voltages related to vehicle operating condition and driving pattern. The methodology and results obtained here give an insight of the relative emission profile of vehicles on a typical route in Nairobi (Kenya). The parSYNC®-PEMS responded to changing vehicle operating condition (turbocharged) and the driving mode (idling, acceleration and deceleration) characterized by the changing VSP. The high resolution data of a few tests confirm the usefulness of parSYNC® in obtaining much needed temporal and spatial tail-pipe PM emission data to characterize the real-world emissions of vehicles. When calibrated with a reference instrument, parSYNC®-PEMS may be used to indicate the relative total PM emissions [mg/km] of different vehicles and determine relative PM emissions during different driving modes. However, the parSYNC®-PEMS sensor voltage relation between all three sensors best worked for the older vehicle (Mercedes Benz) vehicle, which indicates presence of accumulation exhaust particles. Therefore, for diesel vehicles with older technology and under load, this parSYNC®-PEMS would yield most accurate results. This is most useful In Africa, as older diesel fleets are prevalent and are attributable to high PM emissions especially in urban areas. The VSP profile for the vehicles tested in Nairobi was for a profile typical for a heavily congested city with high altitude and steep roads; this increases the pollution load from the vehicle fleet.

A cost effective solution is needed by authorities and governments to tackle the measurement of emissions in Africa vehicle fleets. The high temporal and spatial characterization of emissions exhaust is useful for identifying pollution 'hotspots' useful for planning authorities and governments. The insights gained from this study could aid the generation of PM emission factors for an African urban fleet which in turn can support the design of environmental and transport policy aimed at decreasing on-road PM pollution and improving urban air quality (Zhang, 2006). However, there are a number of caveats that need to be addressed before a wide range of parSYNC®-PEMS applications. Firstly, a larger sample of vehicles, routes and loads need to sampled, secondly, the prototype needs to be calibrated with a reference instrument, thirdly, an assured cost-effective surrogate method to determine exhaust flow rate needs to be developed and lastly, the best fit algorithm for baseline corrections and alignment should be developed for when drifts occur.

On-going or future works include sensor module validation through calibration with a reference instrument to determine the best fit of the combined sensor voltage to the three sensor's voltage readings. The best fit strategy for the parSYNC® PM fit is under development to be possibly based on General Additive Model (GAM) and spline fit model, utilizing a statistical noise reduction method in the R package "mgcv" (Wood, 2017).

2.6 Supplementary

2.6.1 SECTION A: Vehicle specifications and journey narrative during testing

Table S 1: Initial pool of vehicles mounted with parSYNC, OBD scanner and GPS system from which the test vehicles were selected

Number of Test	Date	Test Sheet	Vehicle Type	parSYNC	GPS	OBD
Test 1	04/05/2015	✓	ToyotaRav4	✓	✓	X
Test 2	04/05/2015	✓	Mercedes Diesel	✓	X	✓
Test 3	05/05/2015	✓	Toyota Fielder	✓	X	X
Test 4	05/05/2015	✓	Toyota Landcruiser	✓	X	X
Test 5	06/05/2015	✓	Toyota Fielder NZE	✓	X	✓
Test 6	11/05/2015	✓	Isuzu Matatu 51	✓	✓	X
Test 7	11/05/2015	✓	Isuzu Matatu 33	✓	X	X
Test 8	13/05/2015	✓	Mitsubishi Shogun	✓	✓	✓
Test 9	13/05/2015	✓	Mitsubishi Shogun	✓	✓	✓
Test 10	16/05/2015	✓	Mercedes Diesel	✓	✓	✓
Test 11	16/05/2015	✓	Mercedes Diesel	✓	✓	✓
Test 12	18/05/2015	✓	Isuzu Matatu 29	✓	✓	X
Test 13	18/05/2015	✓	Isuzu Matatu 29	✓	✓	X
Test 14	18/05/2015	✓	Isuzu Matatu 29	✓	✓	X
Test 15	21/05/2015	✓	Ford Focus	✓	✓	✓

Table S 2: VEHICLE SPECIFICATIONS AND JOURNEY NARRATIVE Test 8, 9, 10, 11

	Test 8	**Test 9**
Type of vehicle	Private	Private
Diameter of exhaust (CM)	4.8	4.8
Fuel	Diesel	Diesel
Manufacturer	MITSUBISHI	MITSUBISHI
Model of vehicle	SHOGUN	SHOGUN
Transmission	AUTOMATIC	AUTOMATIC
Engine Size (cc)	3200	3200
Gross Value Weight (KG)	2255	2255
Fuel Tank Volume (L)	80	80
Year of Manufacture	2007	2007
Odometer reading (initial) miles	94117	94150
Odometer reading (Final) miles	94150	94182
Initial time	11:33	14:07
Final Time	13:18	15:39
Fuel top up (L)	Tankful	5.30
Route	Predefined route	Predefined route
OBD scanner	YES	YES

	Test 10	**Test 11**
Type of vehicle	Private	Private
Diameter of exhaust (CM)	5.3	5.3
Fuel	Diesel	Diesel
Manufacturer	MERCEDES	MERCEDES
Model of vehicle	ML270 CDI	ML270 CDI
Transmission	MANUAL	MANUAL
Engine Size (cc)	2700	2700
Gross Value Weight (KG)	2870	2870
Fuel Tank Volume (L)	80	80
Year of Manufacture	2002	2002
Odometer reading (initial) (km)	143045	143100
Odometer reading (Final) (km)	143099	143152
Initial time	13:08	16:01
Final Time	14:59	18:22
Fuel top up (L)	FULL TANK	6.31
Route	Predefined route	Predefined route
OBD scanner	YES	YES

2.6.2 SECTION B: Supplementary results

“ROLLING BAL”CORRECTION FOR ALL SENSOR VOLTAGE WITH DIFFERENT WINDOW LENGTH

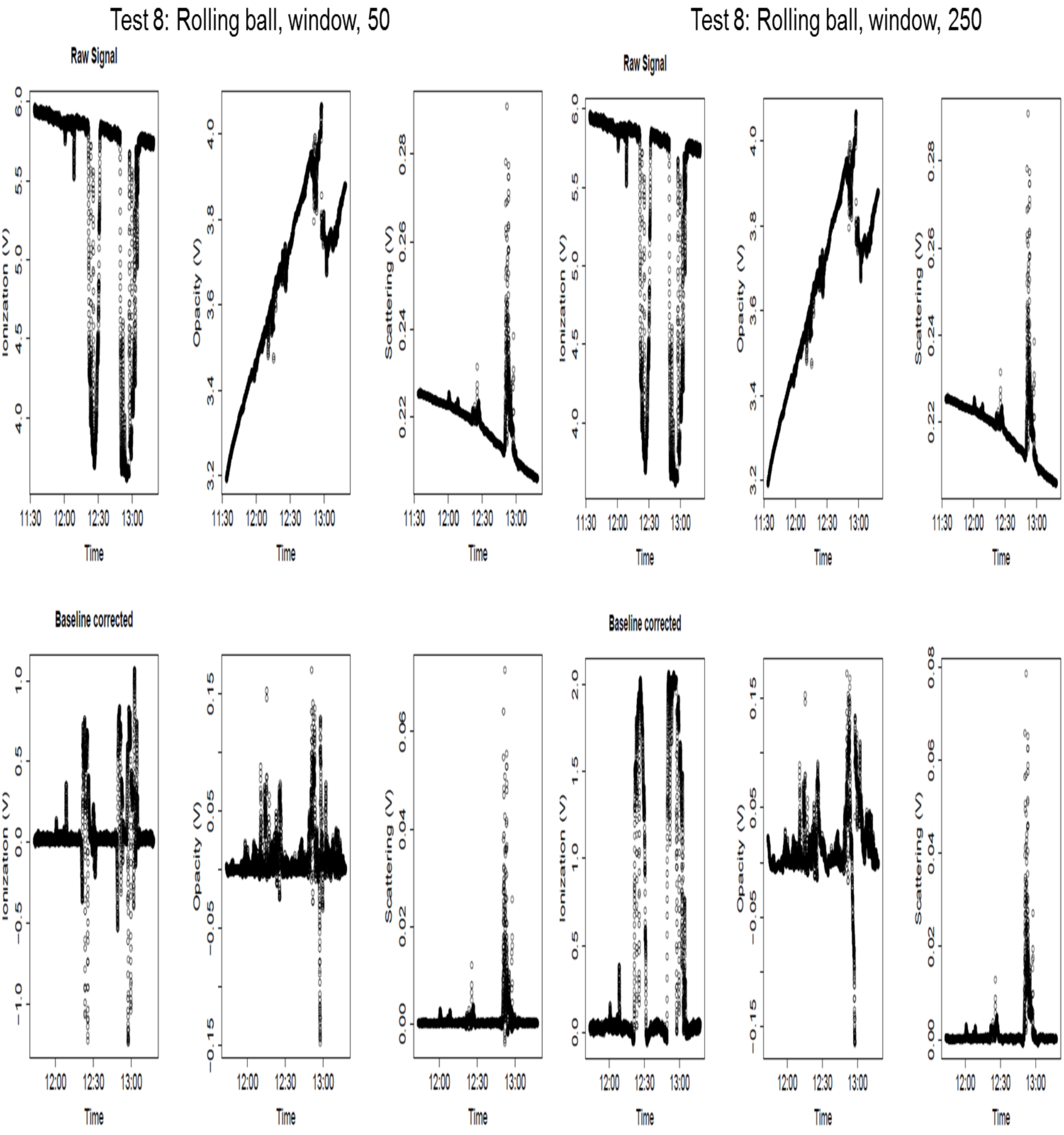


Figure S 3: Raw signal compared to the baseline corrected signal for scattering, opacity and ionization sensor for ‘rolling ball’ window length 50 and 250 for Test 8.

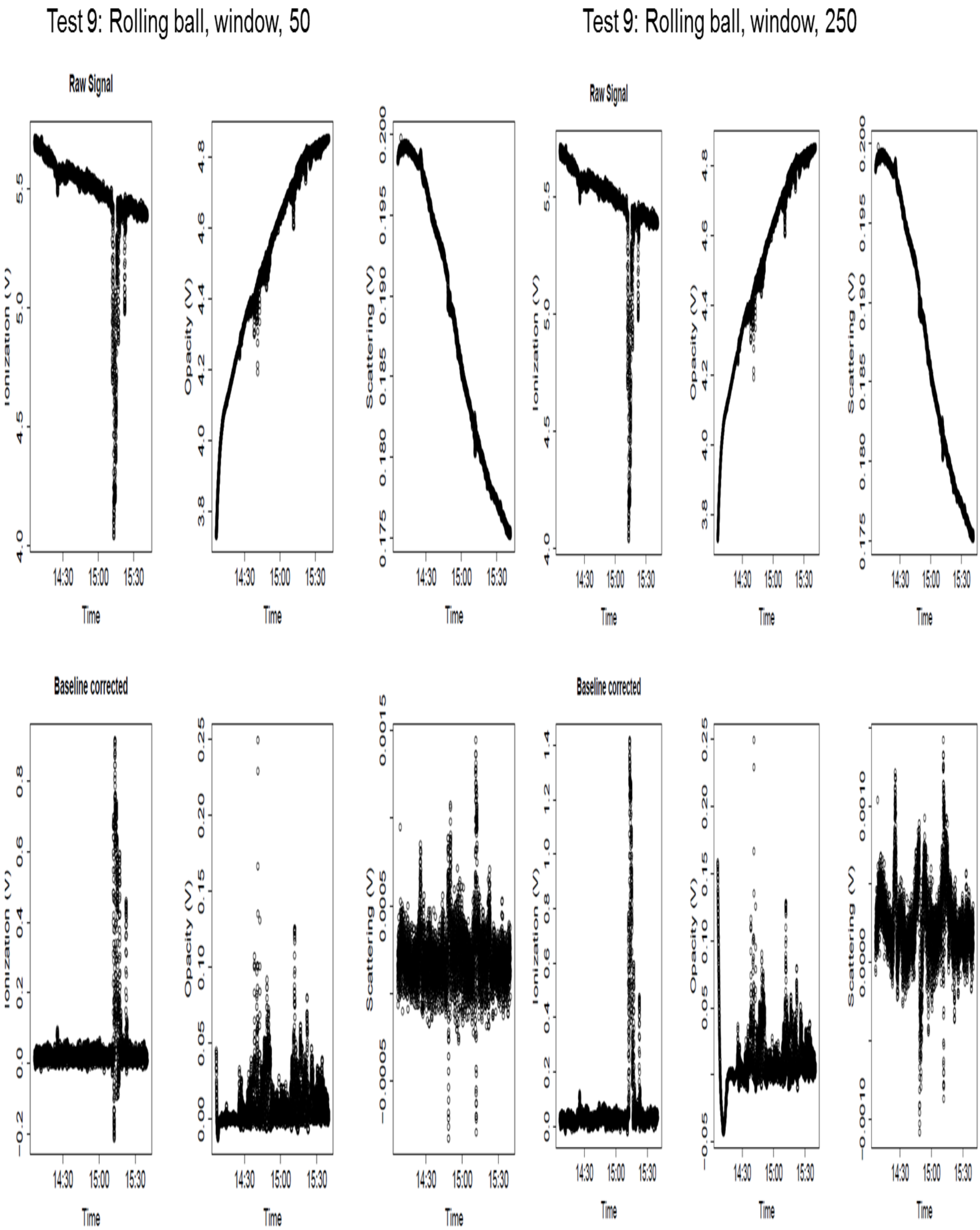


Figure S 4: Raw signal compared to the baseline corrected signal for scattering, opacity and ionization sensor for 'rolling ball' window length 50 and 250 for Test 9.

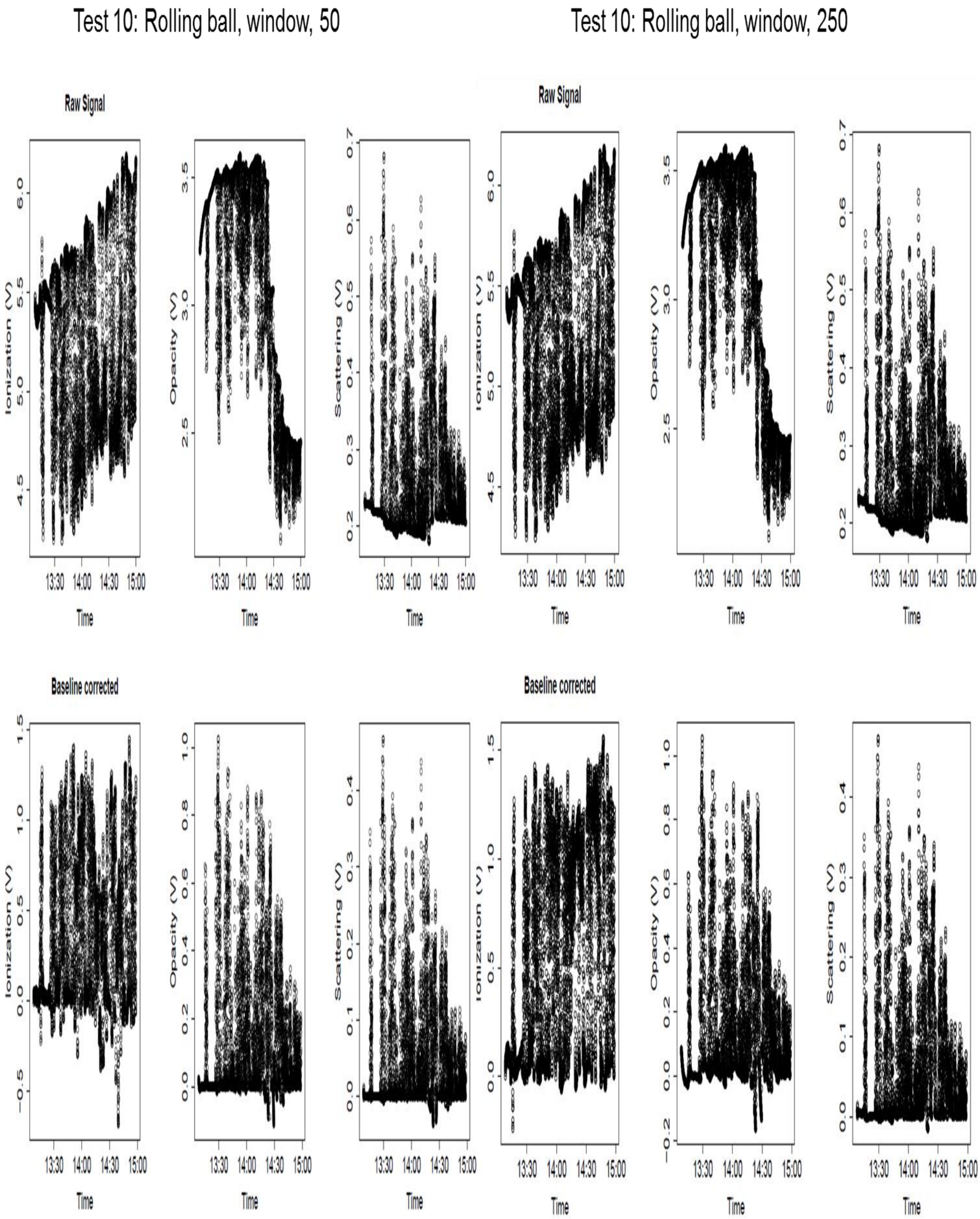


Figure S 5: Raw signal compared to the baseline corrected signal for scattering, opacity and ionization sensor for 'rolling ball' window length 50 and 250 for Test 10.

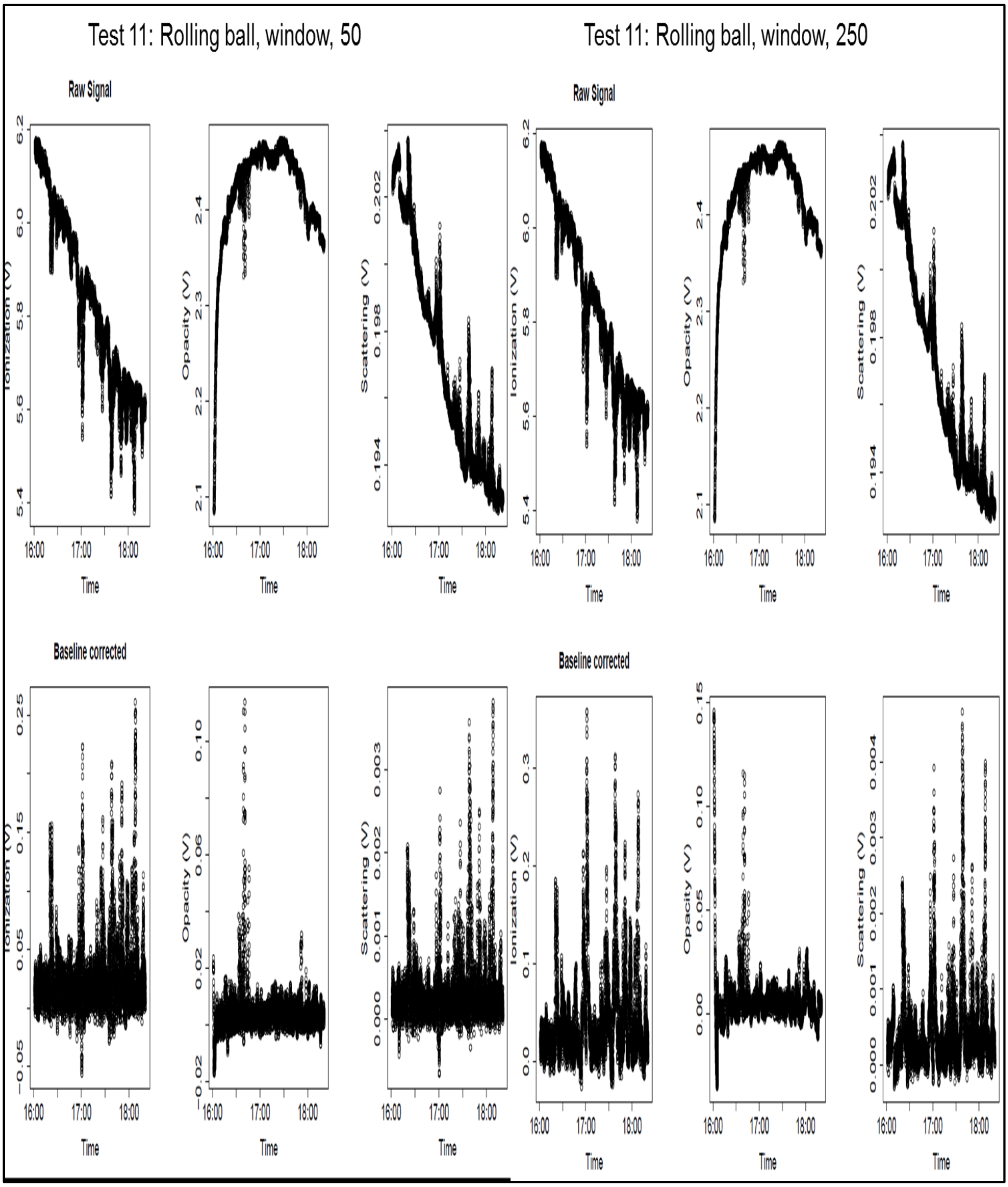


Figure S 6: Raw signal compared to the baseline corrected signal for scattering, opacity and ionization sensor for 'rolling ball' window length 50 and 250 for Test

SENSOR VOLTAGE TIME ALIGNMENT AND BASELINE CORRECTION RESULTS

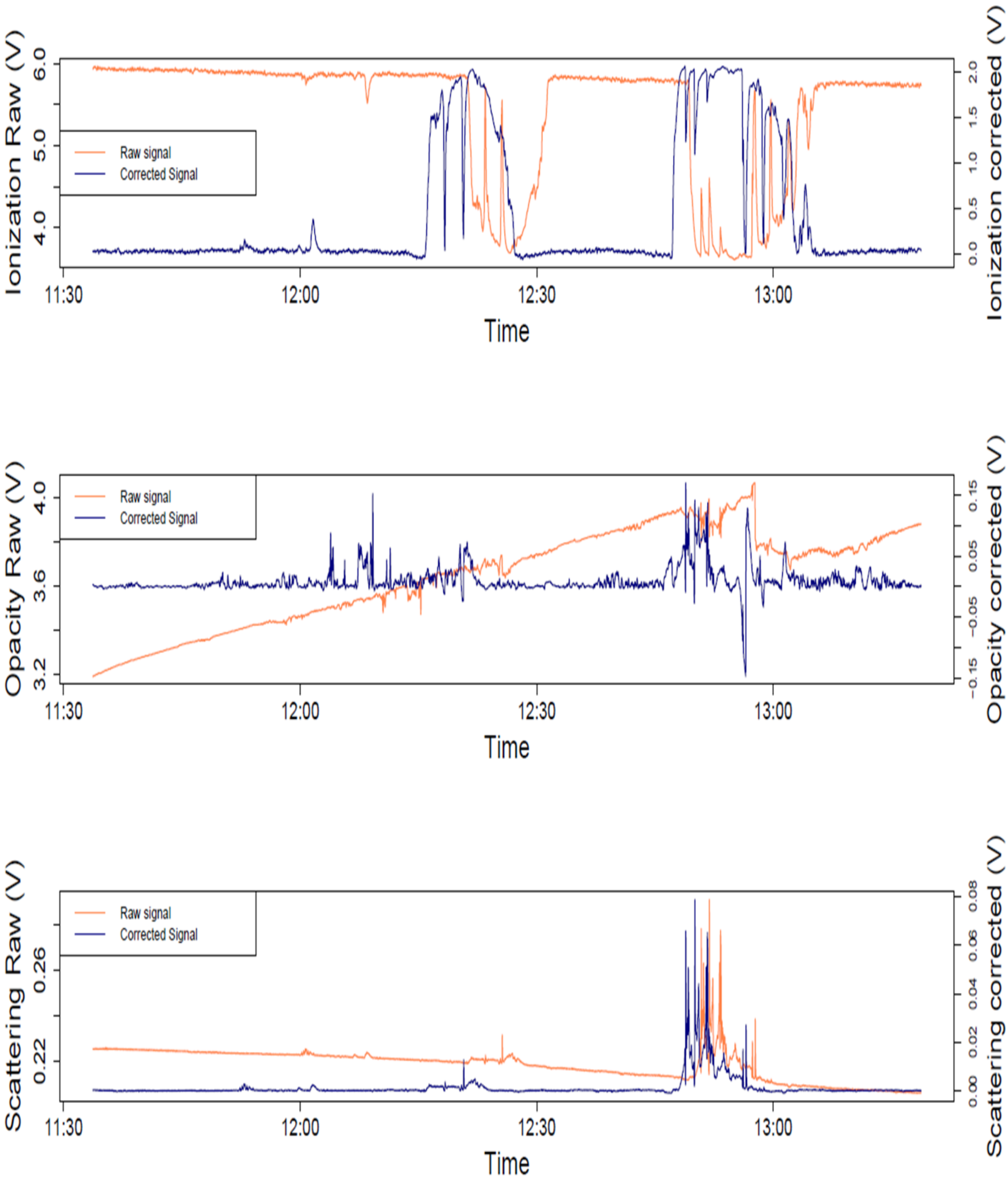


Figure S 7: Raw signal compared to the baseline corrected signal for scattering, opacity and ionization sensor for Test 8

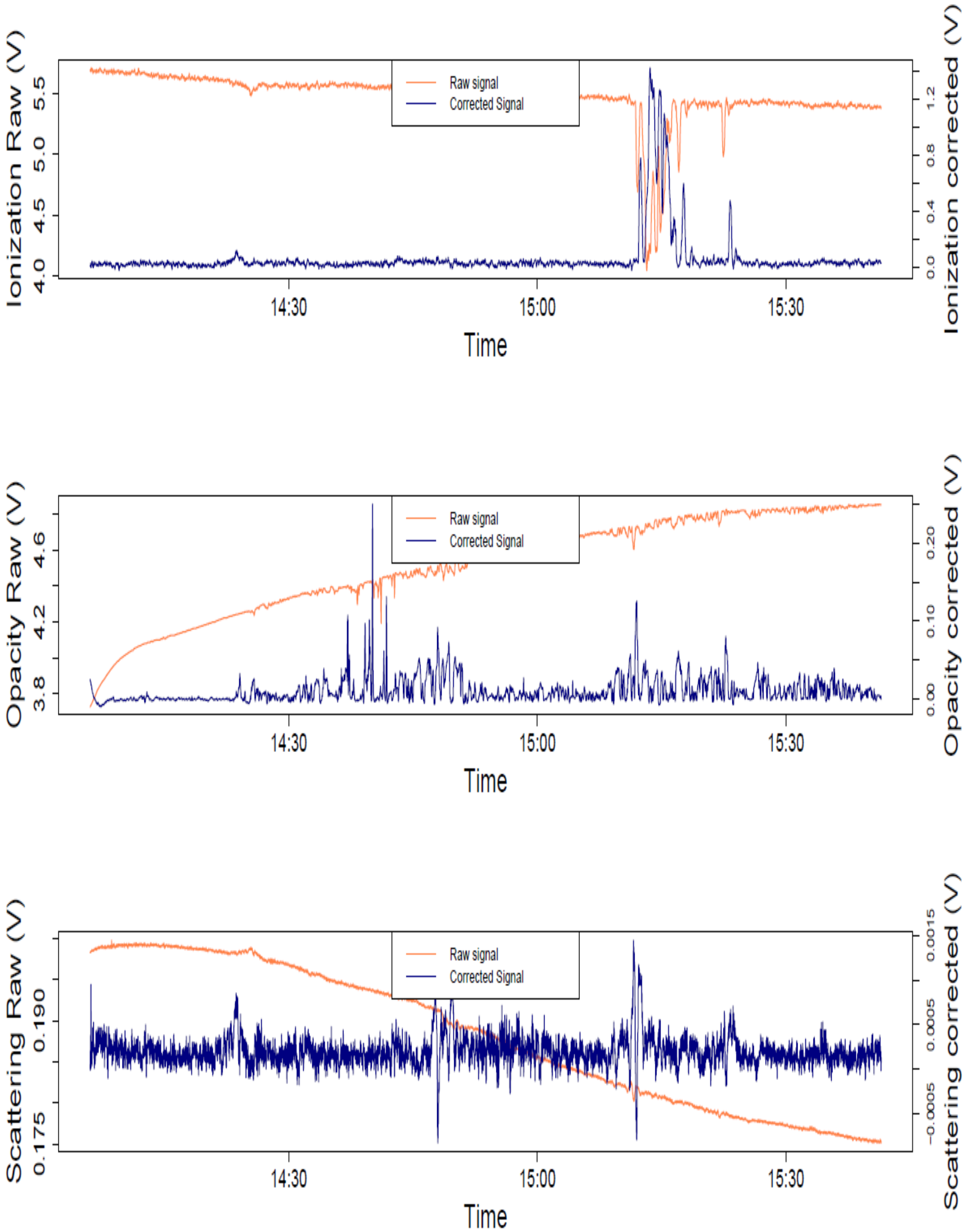


Figure S 8: Raw signal compared to the baseline corrected signal for scattering, opacity and ionization sensor for Test 9

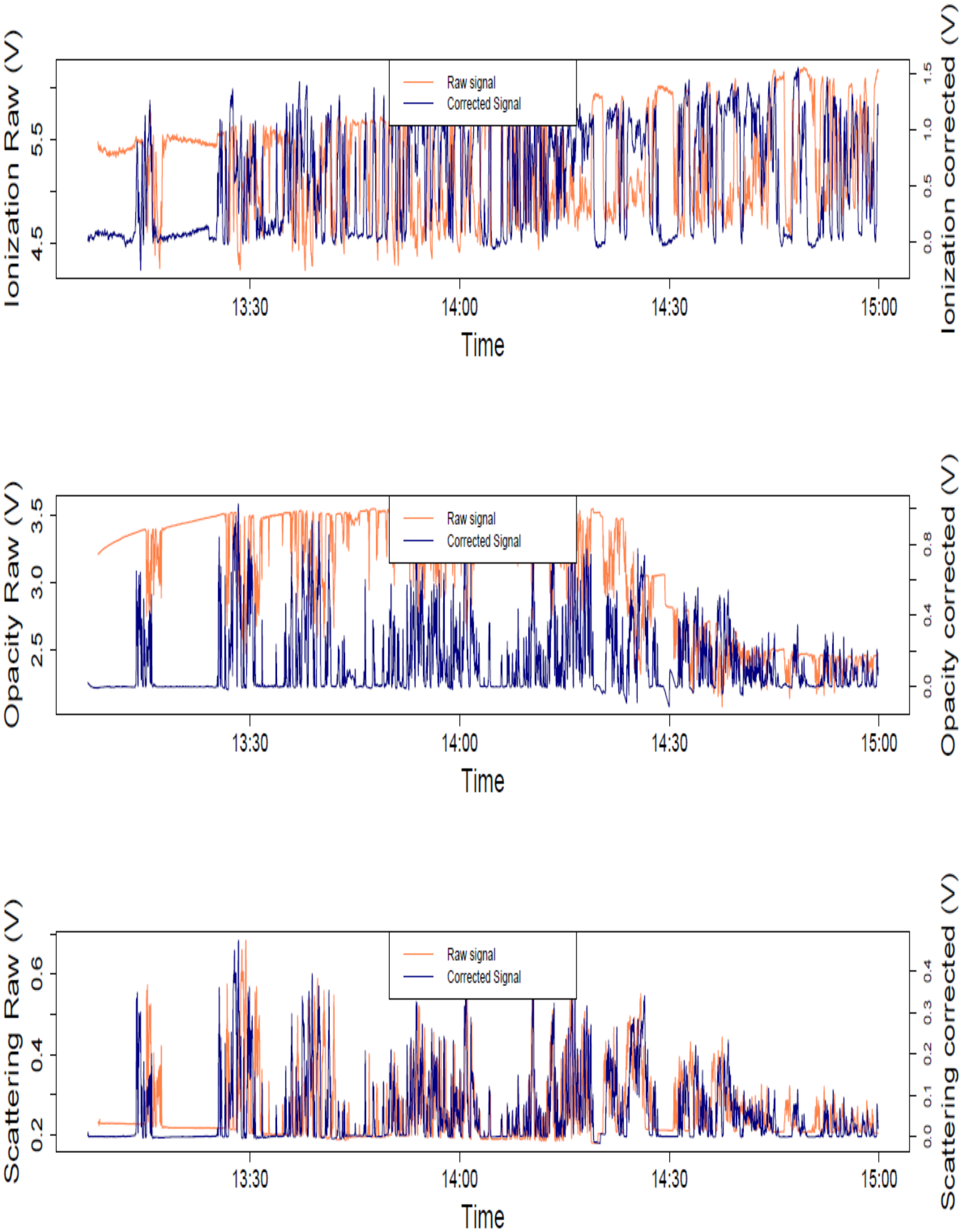


Figure S 9: Raw signal compared to the baseline corrected signal for scattering, opacity and ionization for Test 10

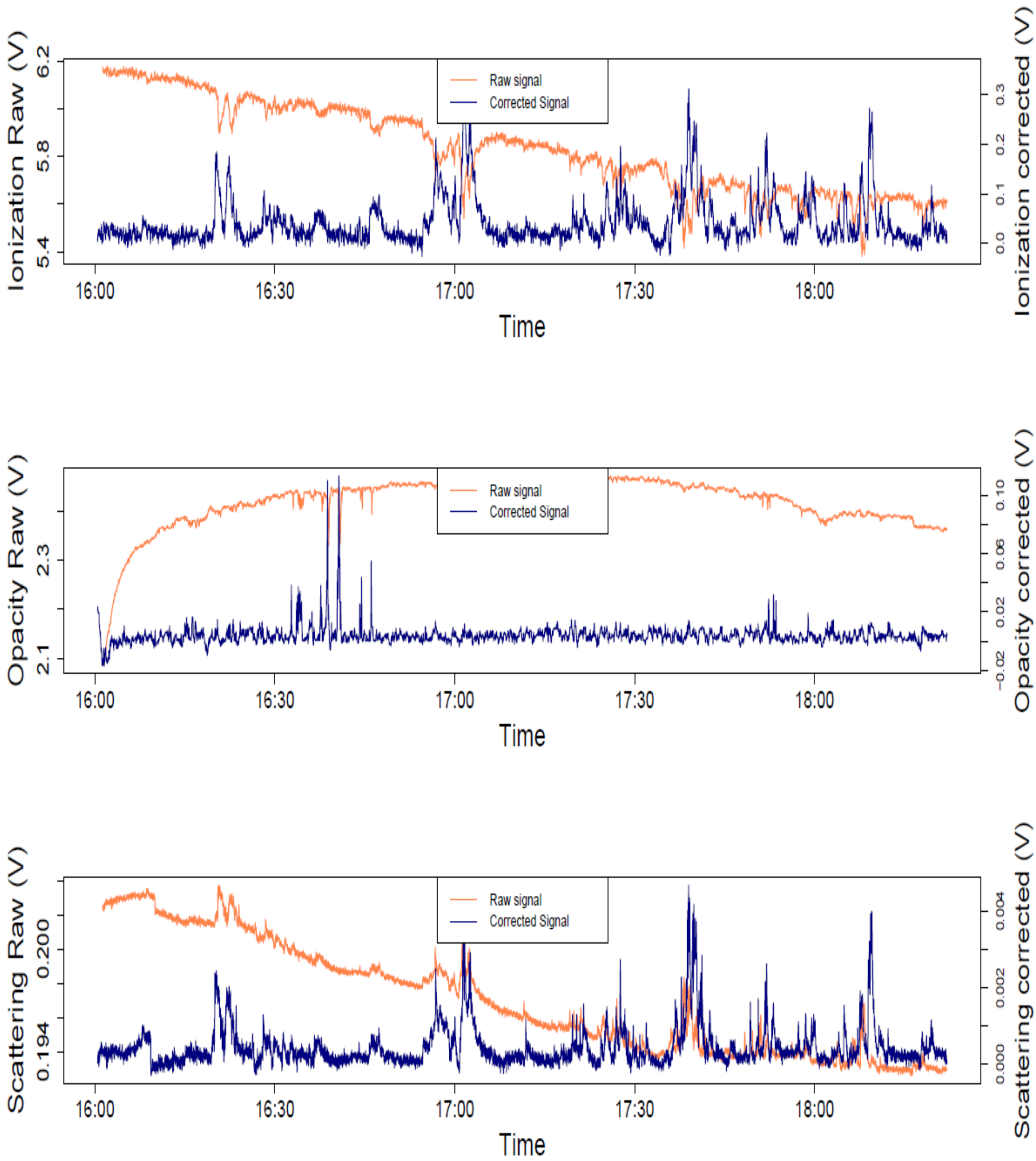


Figure S 10: Raw signal compared to the baseline corrected signal for scattering, opacity and ionization sensor for Test 11

SENSOR VOLTAGE VSP CORRELATION ALIGNMNENT RESULTS

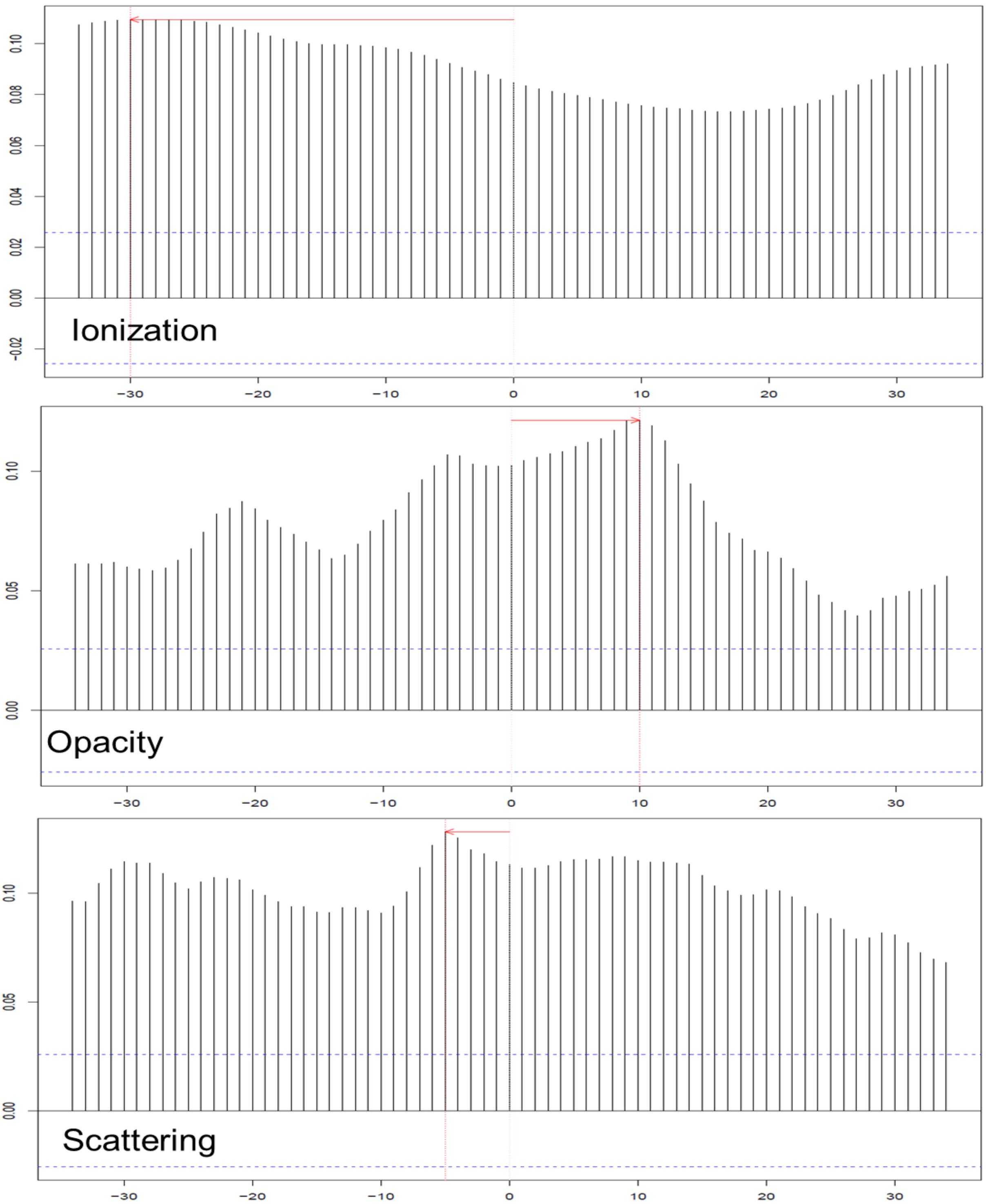


Figure S 11: plot of correlation alignment using pems.utils with VSP from engine data and sensor voltage from (ionization, opacity and scattering) for Test 8 from parSYNC®.

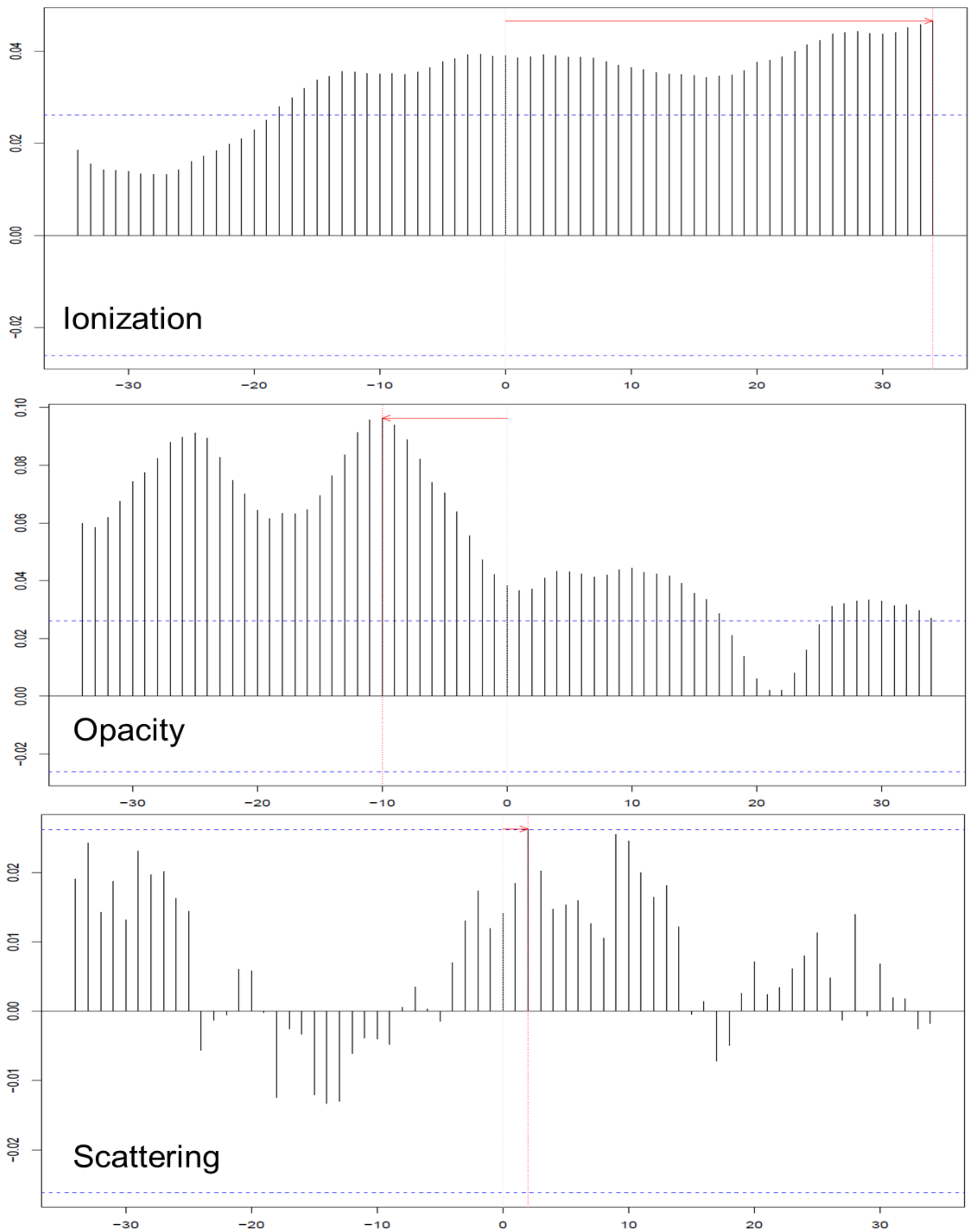


Figure S 12: Plot of correlation alignment using pems.utils with VSP from engine data and sensor voltage from (ionization, opacity and scattering) for Test 9 from parSYNC®.

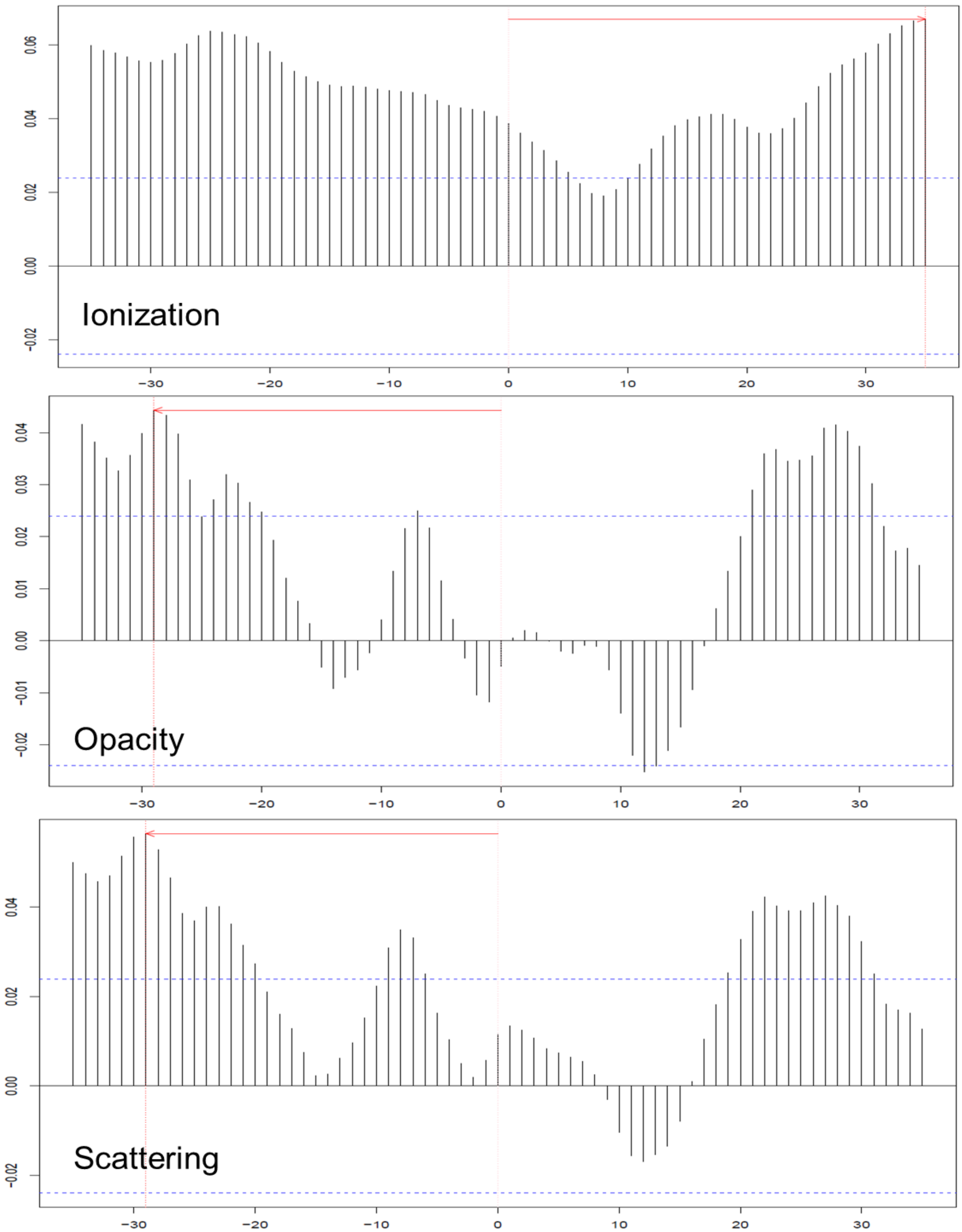


Figure S 13: Plot of correlation alignment using pems.utils with VSP from engine data and sensor voltage from (ionization, opacity and scattering) for Test 10 from parSYNC®.

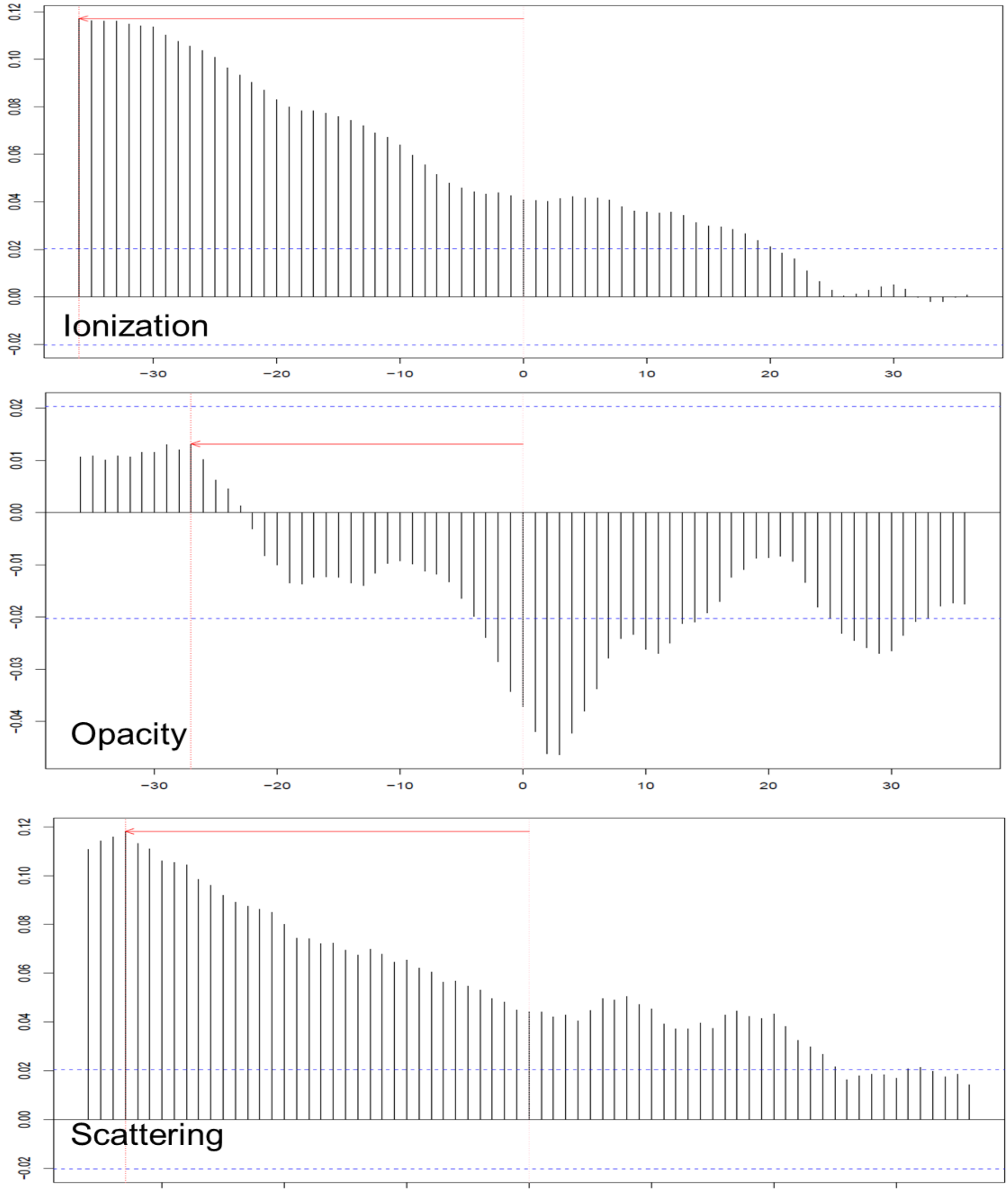


Figure S 14: Plot of correlation alignment using pems.utils with VSP from engine data and sensor voltage from (ionization, opacity and scattering) for Test 11 from parSYNC®.

VEHICLE ACTIVITY DATA DISTRIBUTION AND TIME SERIES

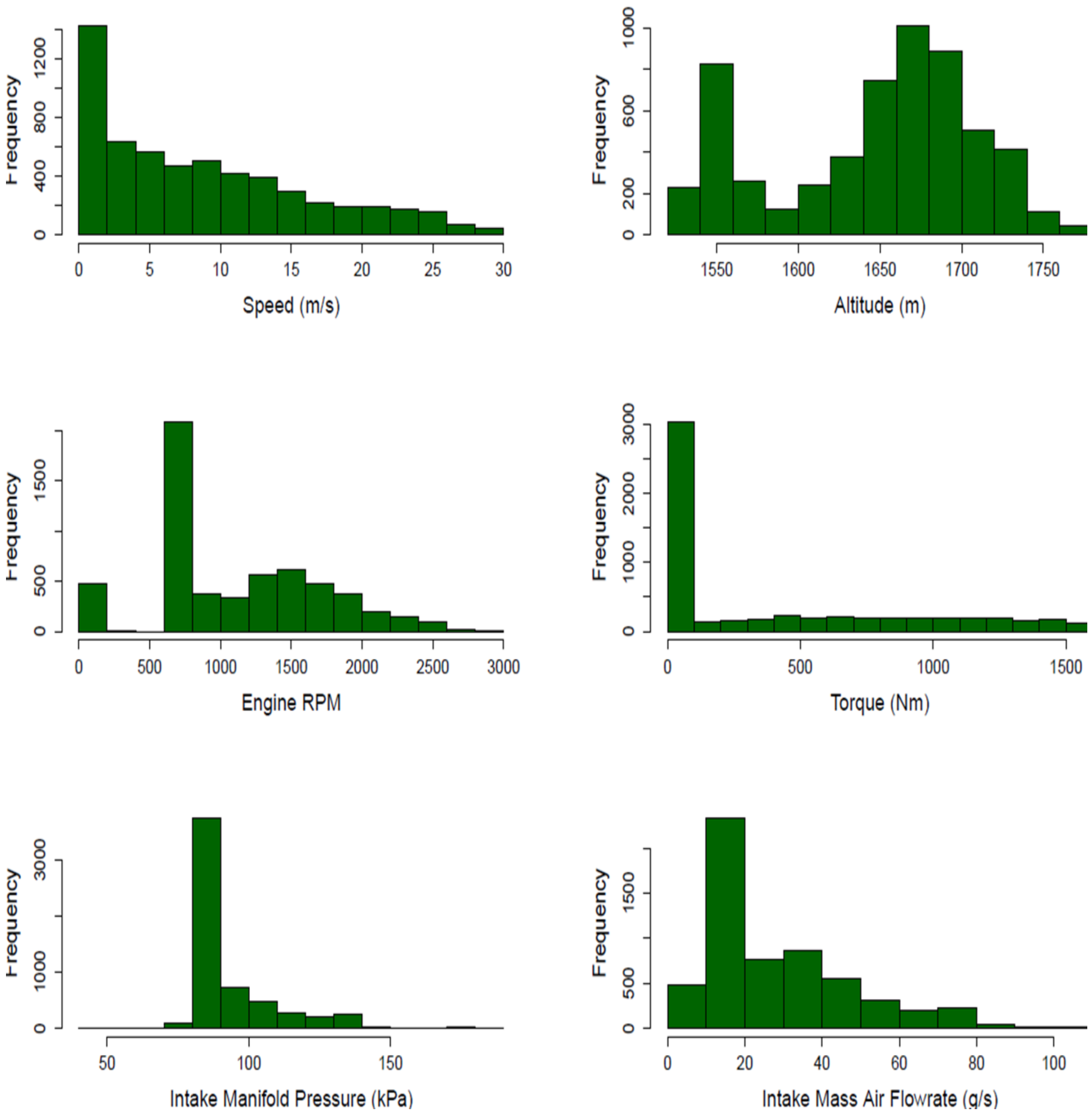


Figure S 15: Distrubution of select engine parameters from Test 8

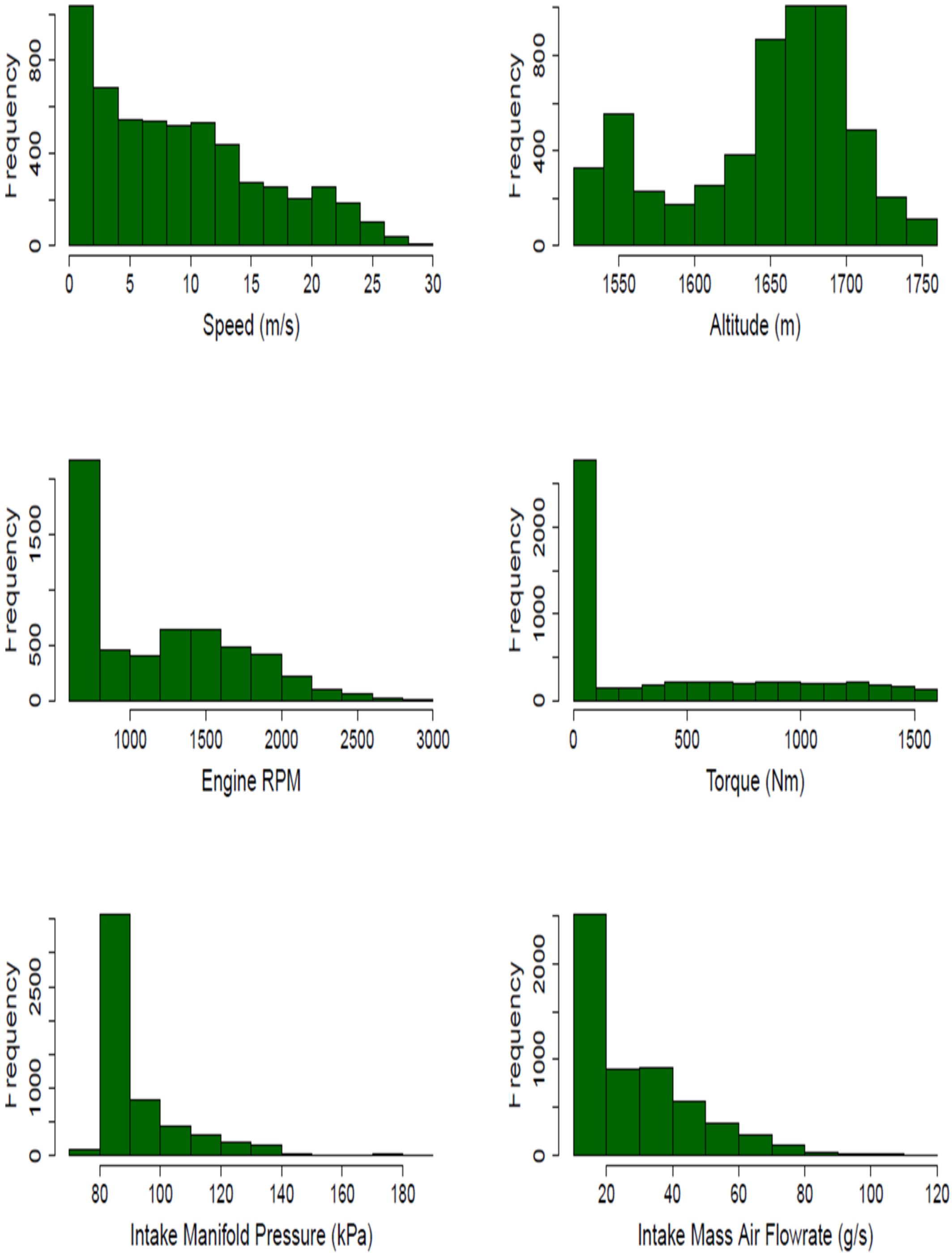


Figure S 16: Distribution of select engine parameters from Test 9

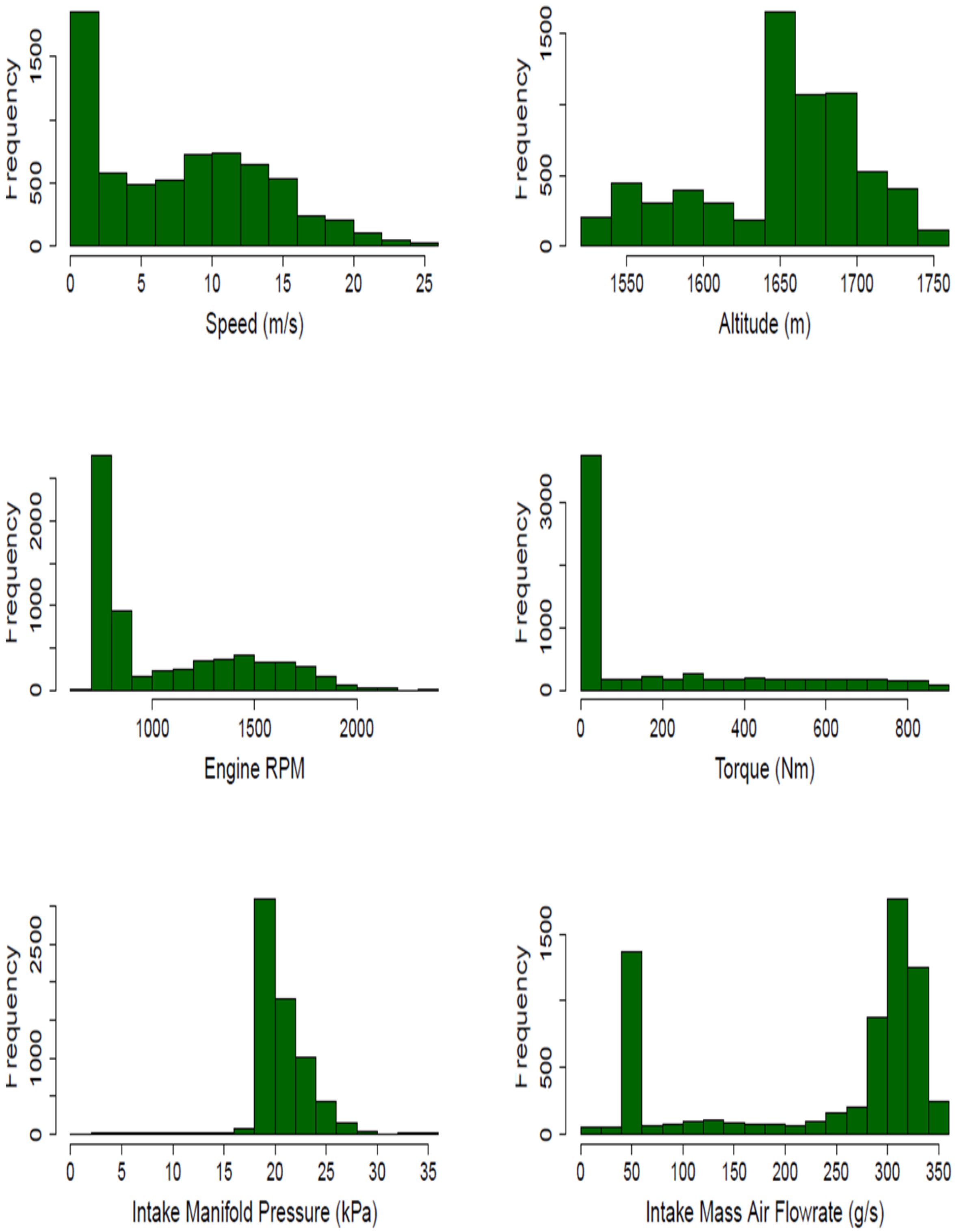


Figure S 17: Distribution of select engine parameters from Test 10

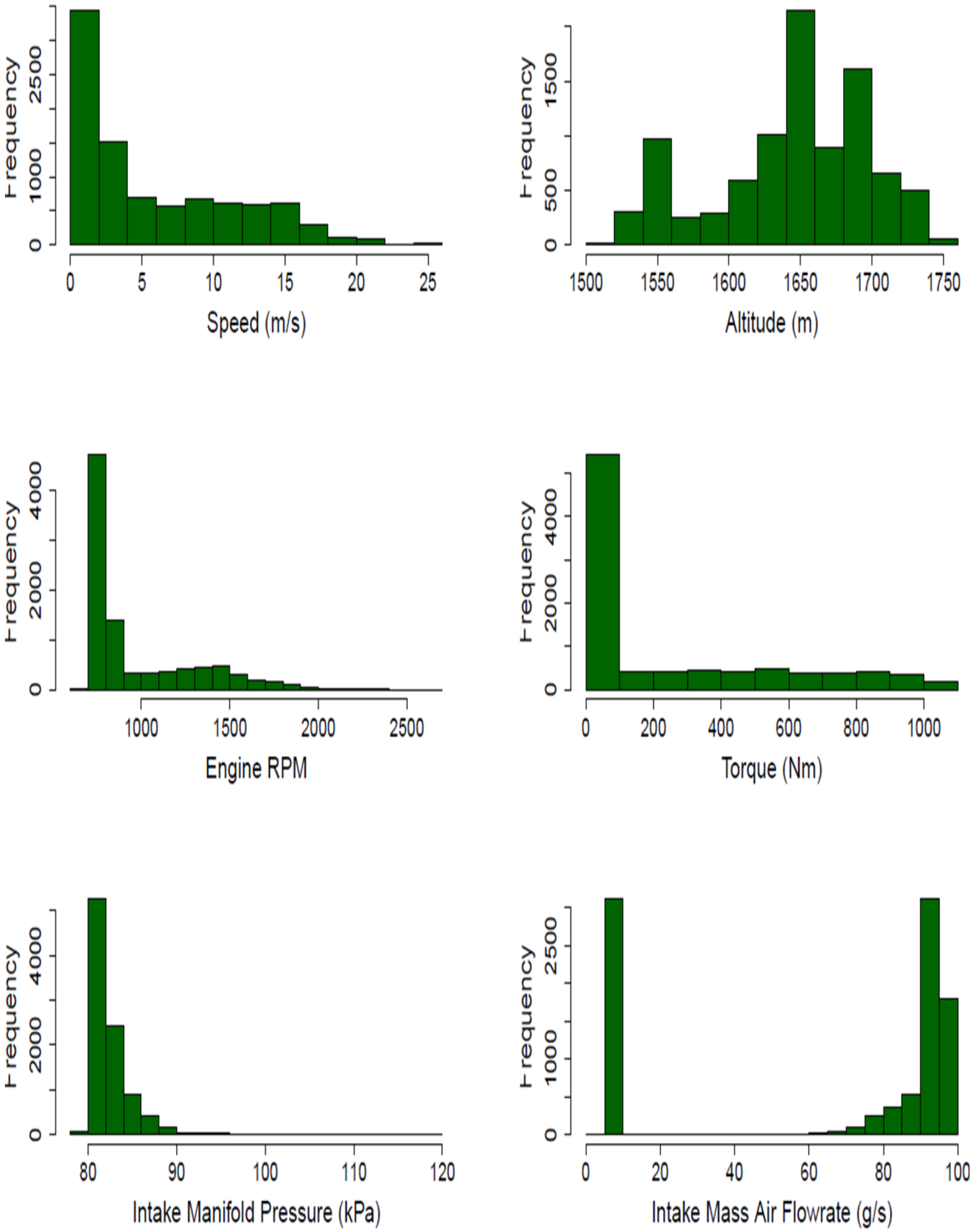


Figure S 18: Distribution of select engine parameters from Test 11

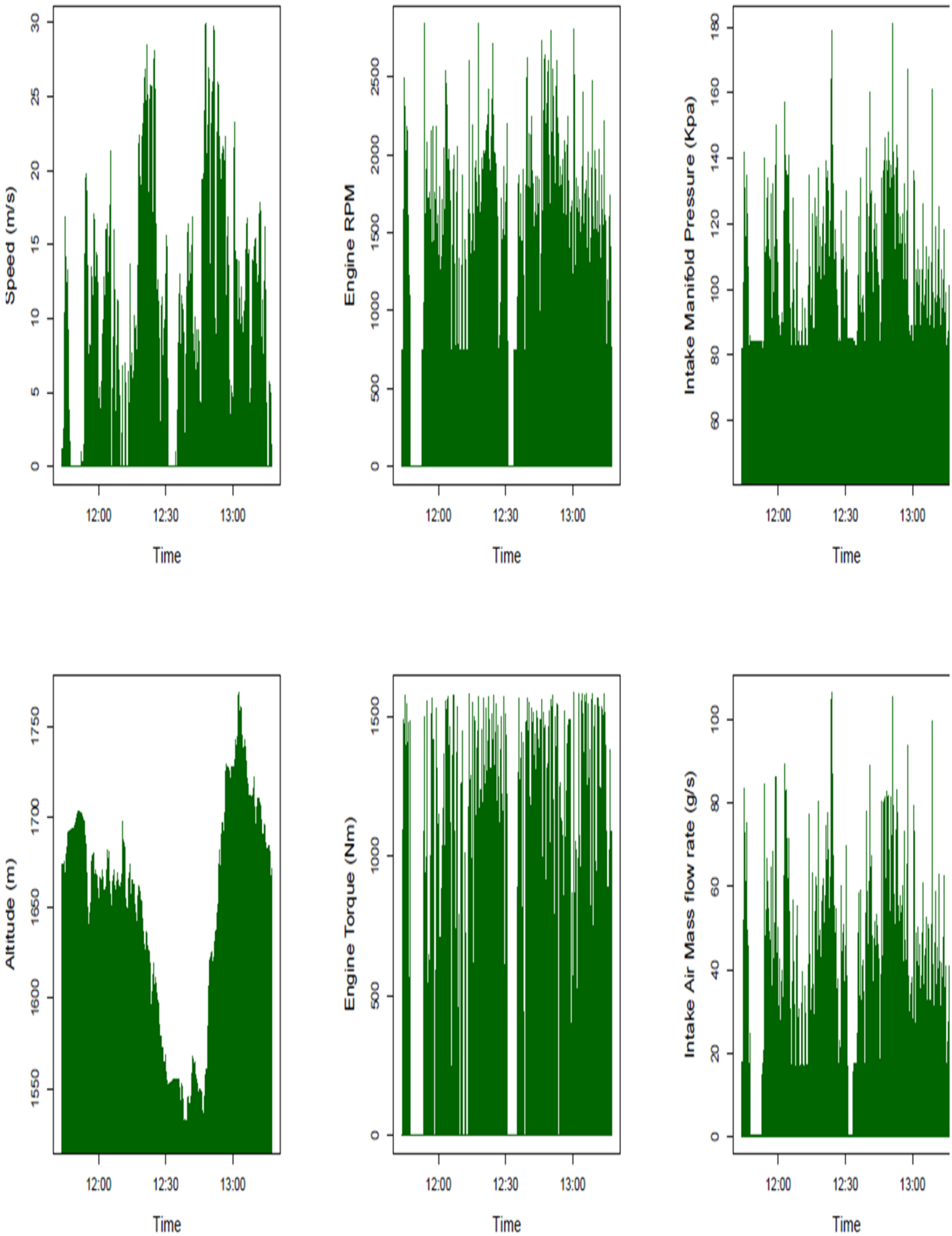


Figure S 19: Select time series of engine parameters for Test 8

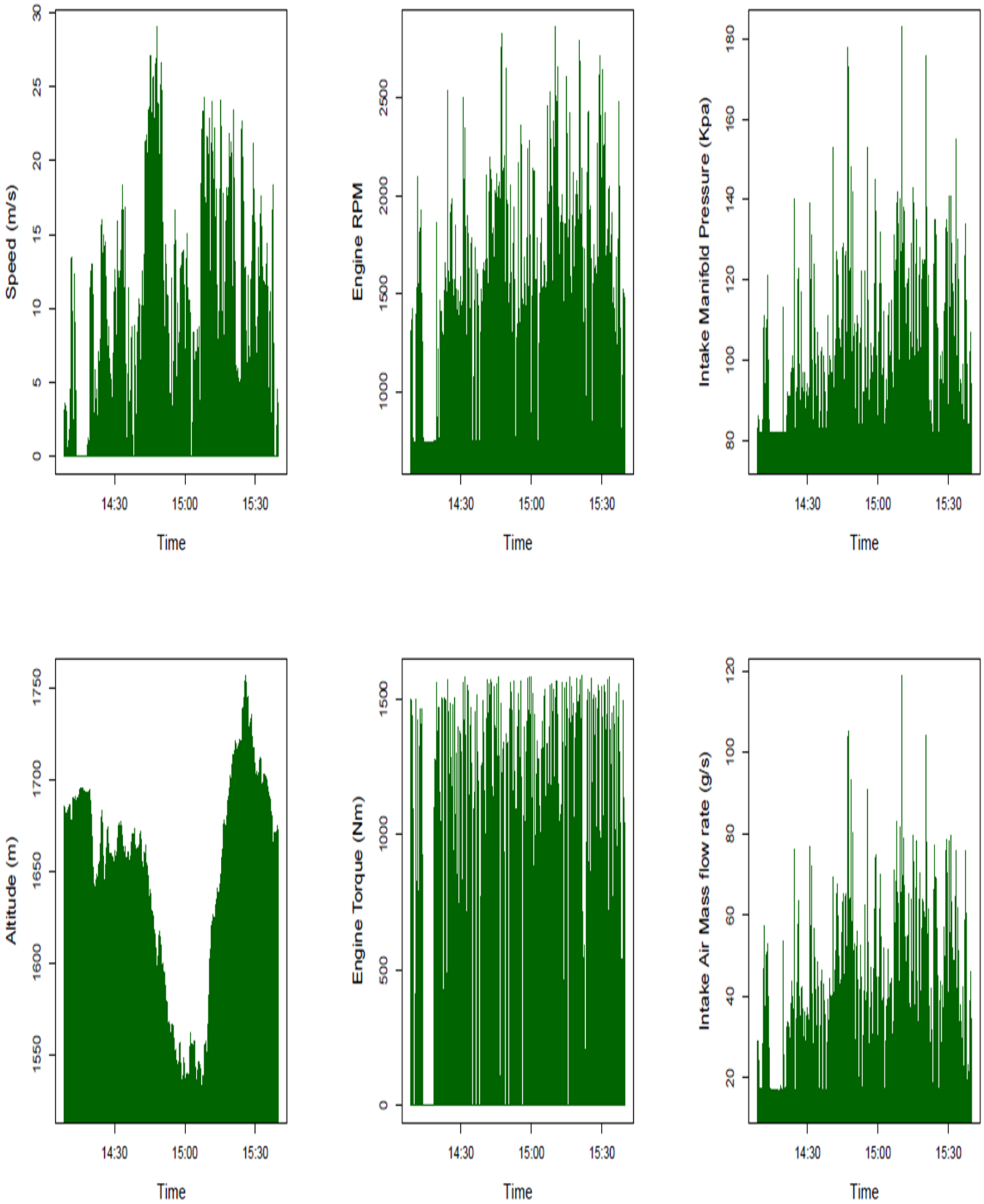


Figure S 20: Select time series of engine parameters for Test 9

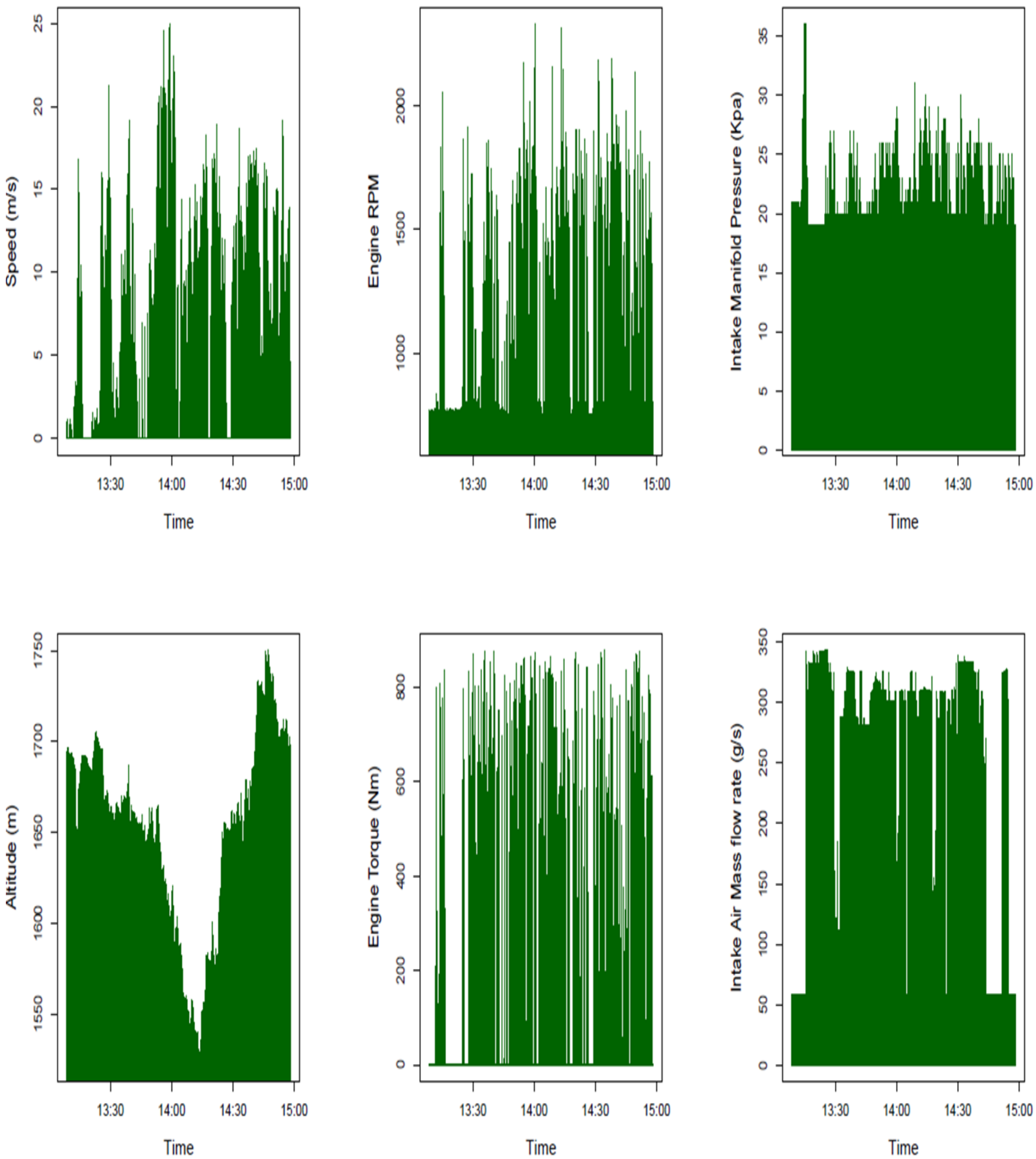


Figure S 21: Select time series of engine parameters for Test 10

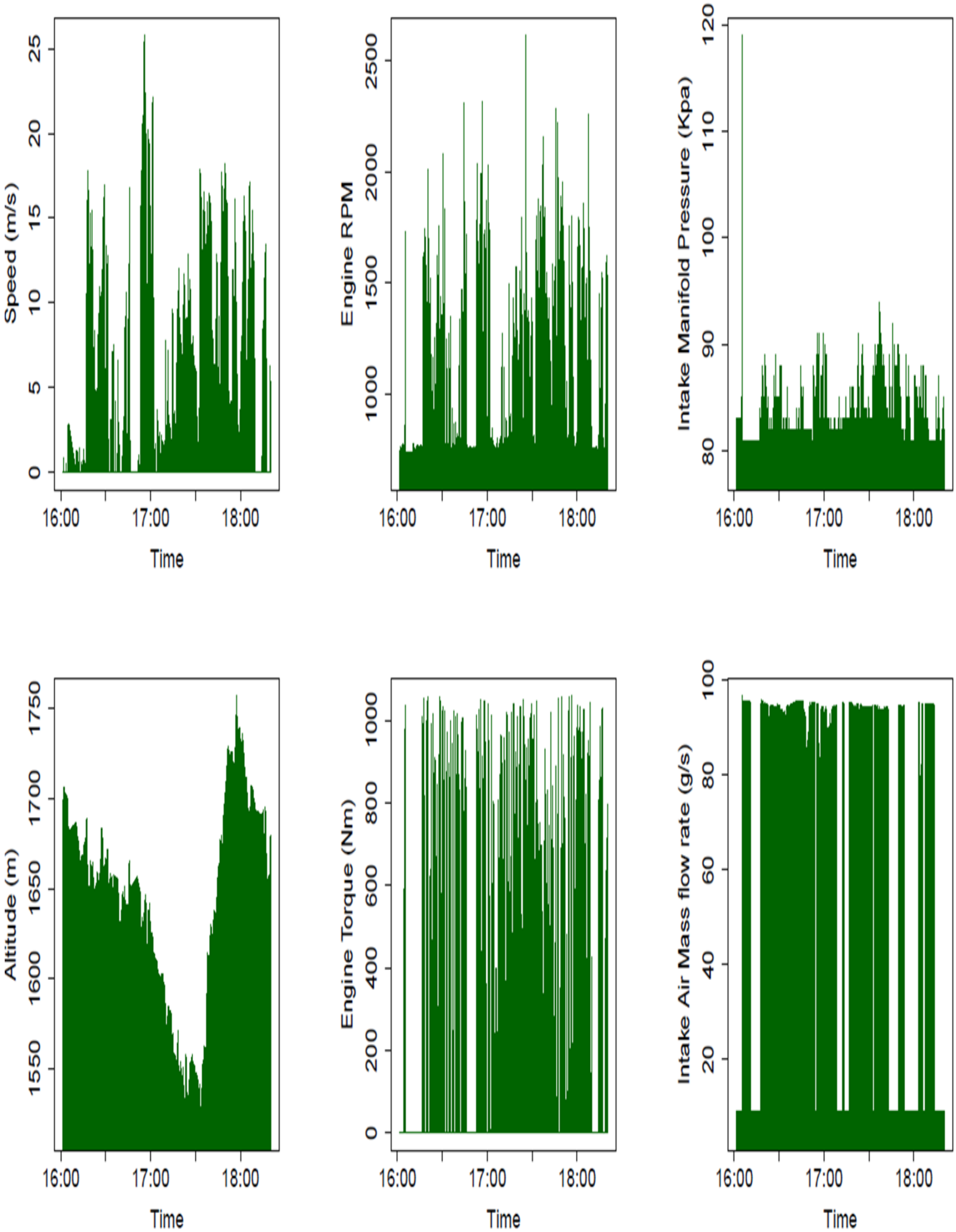


Figure S 22: Select time series of engine parameters for Test 11

SPEED AND ALTITUDE COMPARED TO SENSOR VOLTAGE

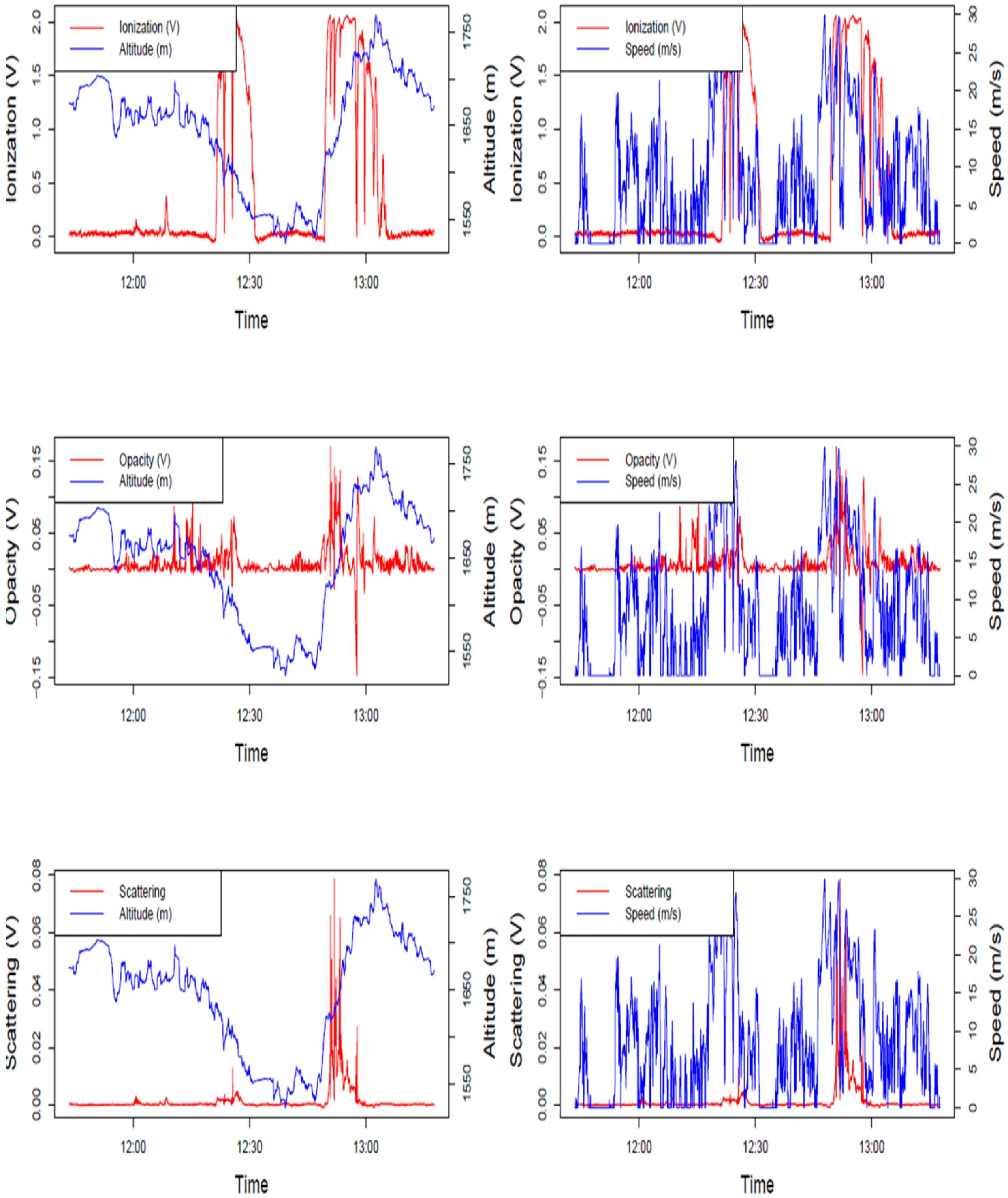


Figure S 23: Speed and altitude compared to sensor voltage (scattering, opacity and ionization) for Test 8

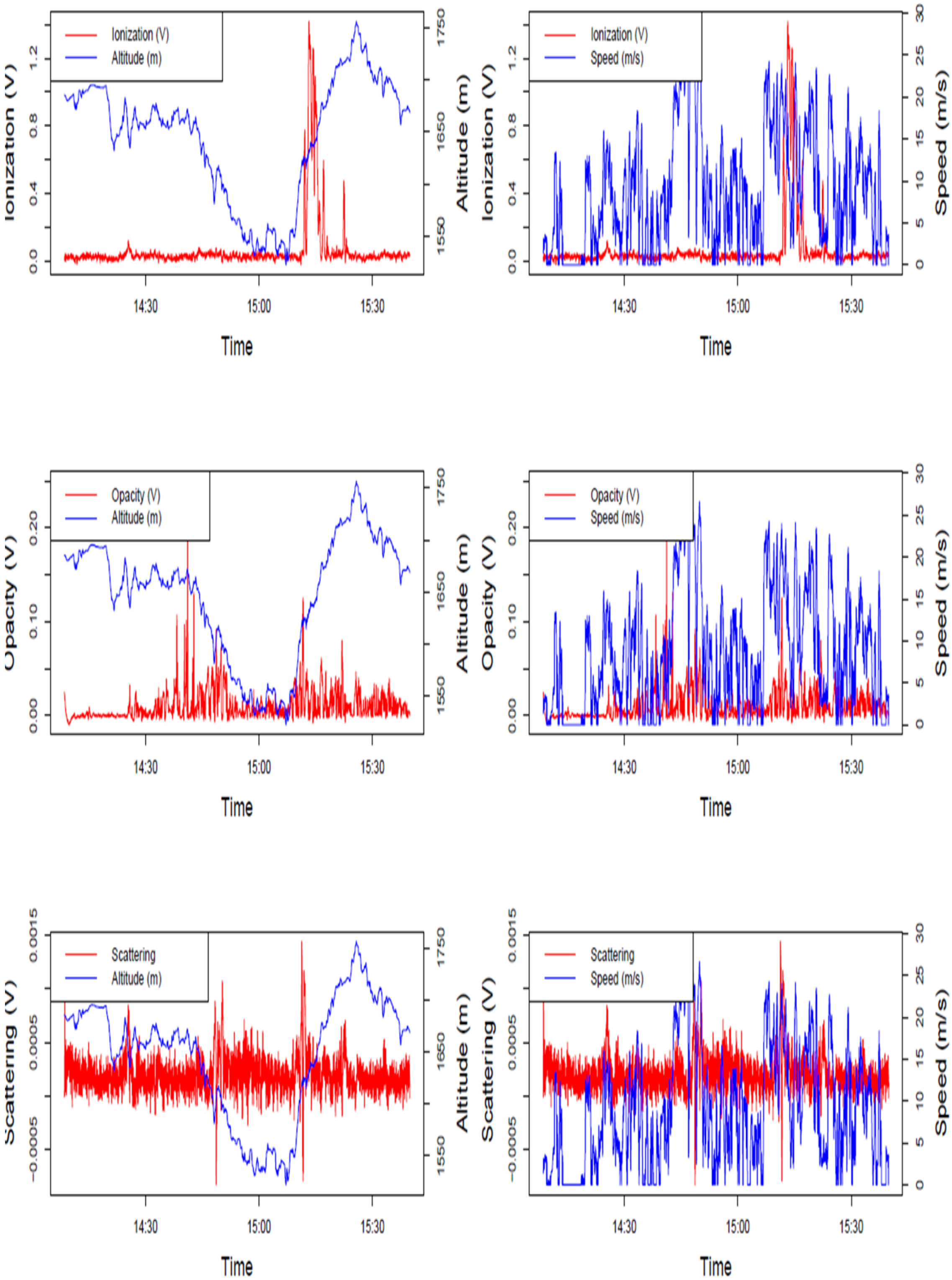


Figure S 24: Speed and altitude compared to sensor voltage (scattering, opacity and ionization) for Test 9

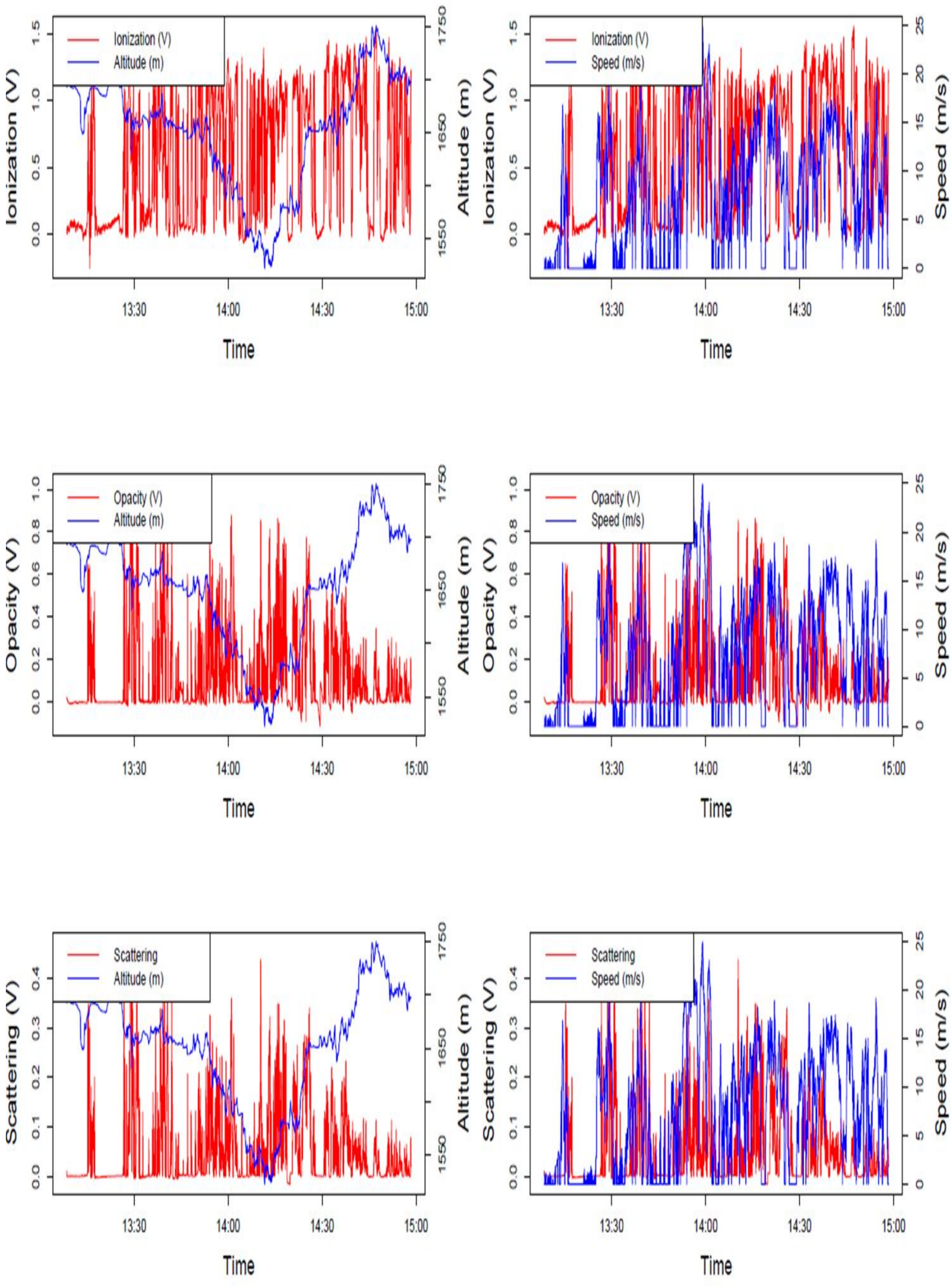


Figure S 25: Speed and altitude compared to sensor voltage (scattering, opacity and ionization) for Test 10

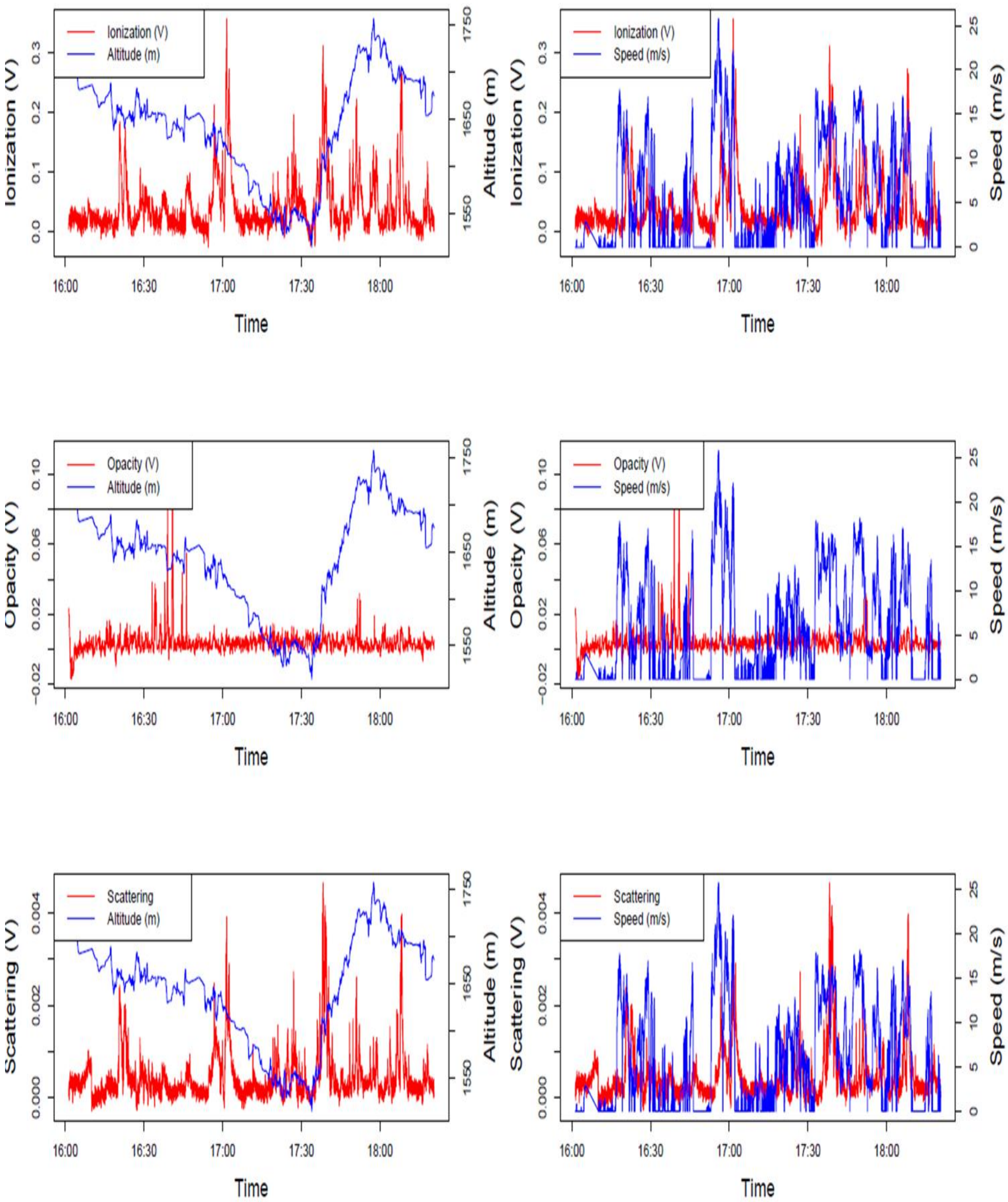


Figure S 26: Speed and altitude compared to sensor voltage (scattering, opacity and ionization) for Test 11

DISTRIBUTION OF VSP AND VARIABLES DETERMINING VSP

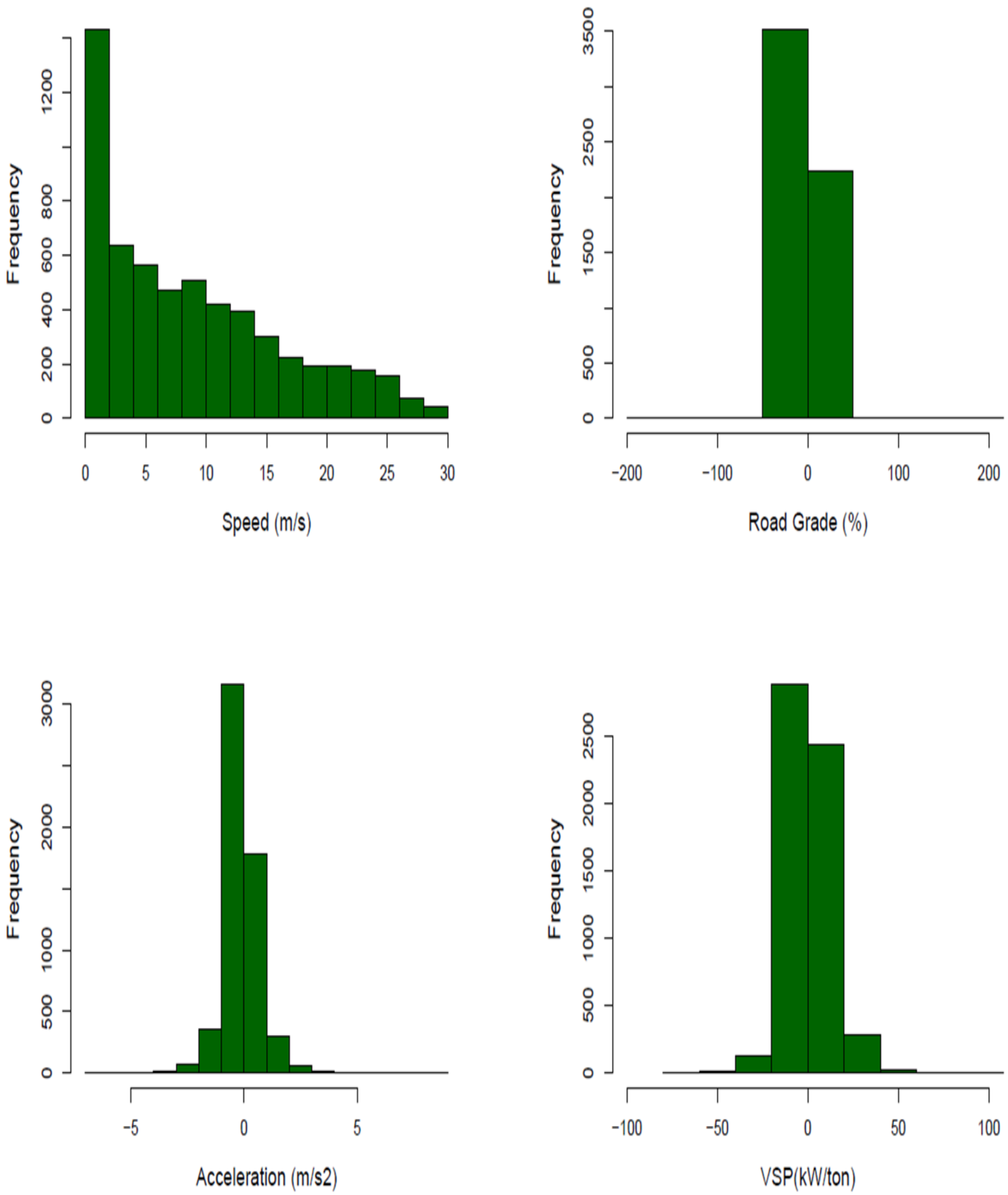


Figure S 27: Distribution of variables determining VSP and VSP for Test 8

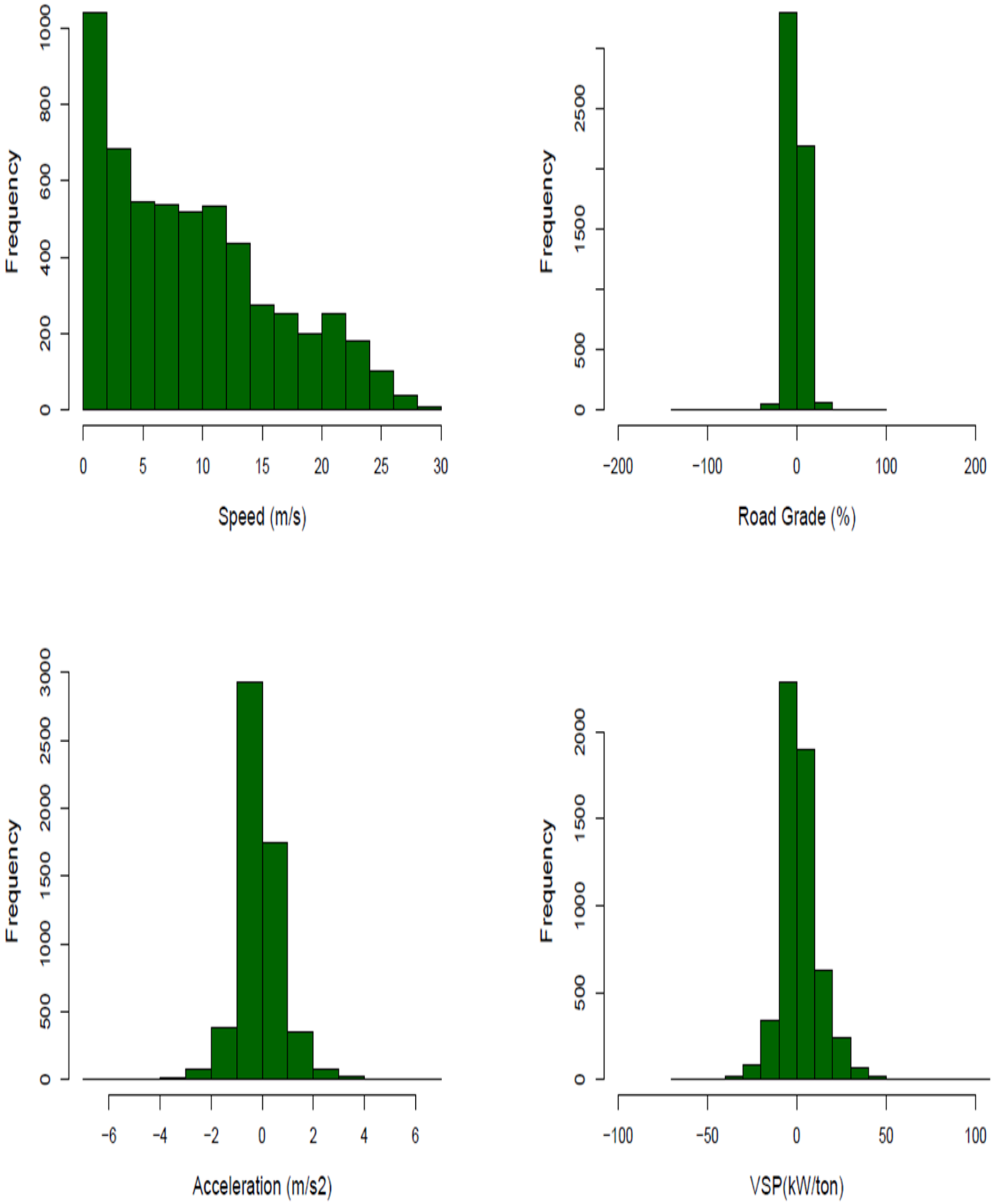


Figure S 28: Distribution of variables determining VSP and VSP for Test 9

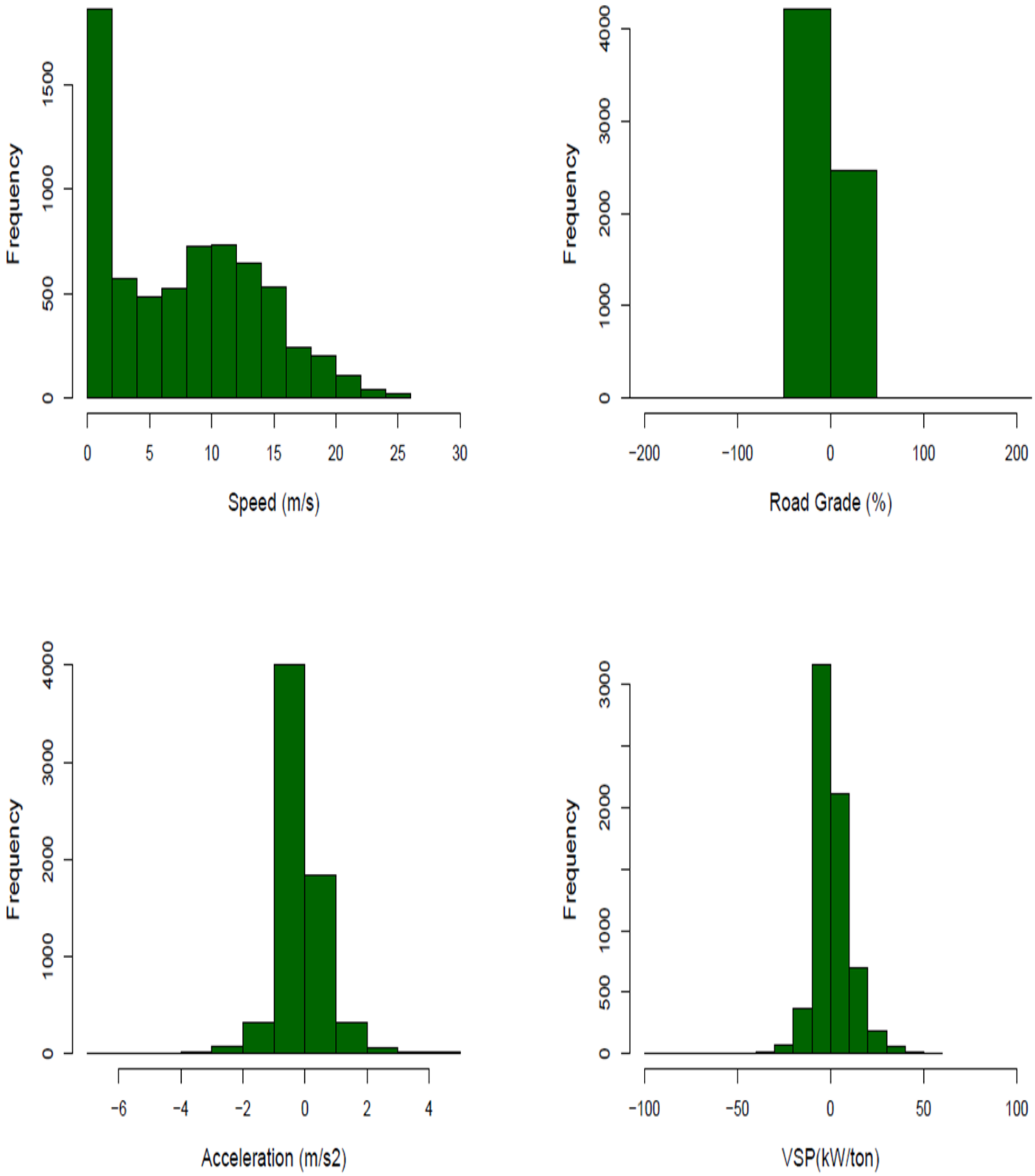


Figure S 29: Distribution of variables determining VSP and VSP for Test 10

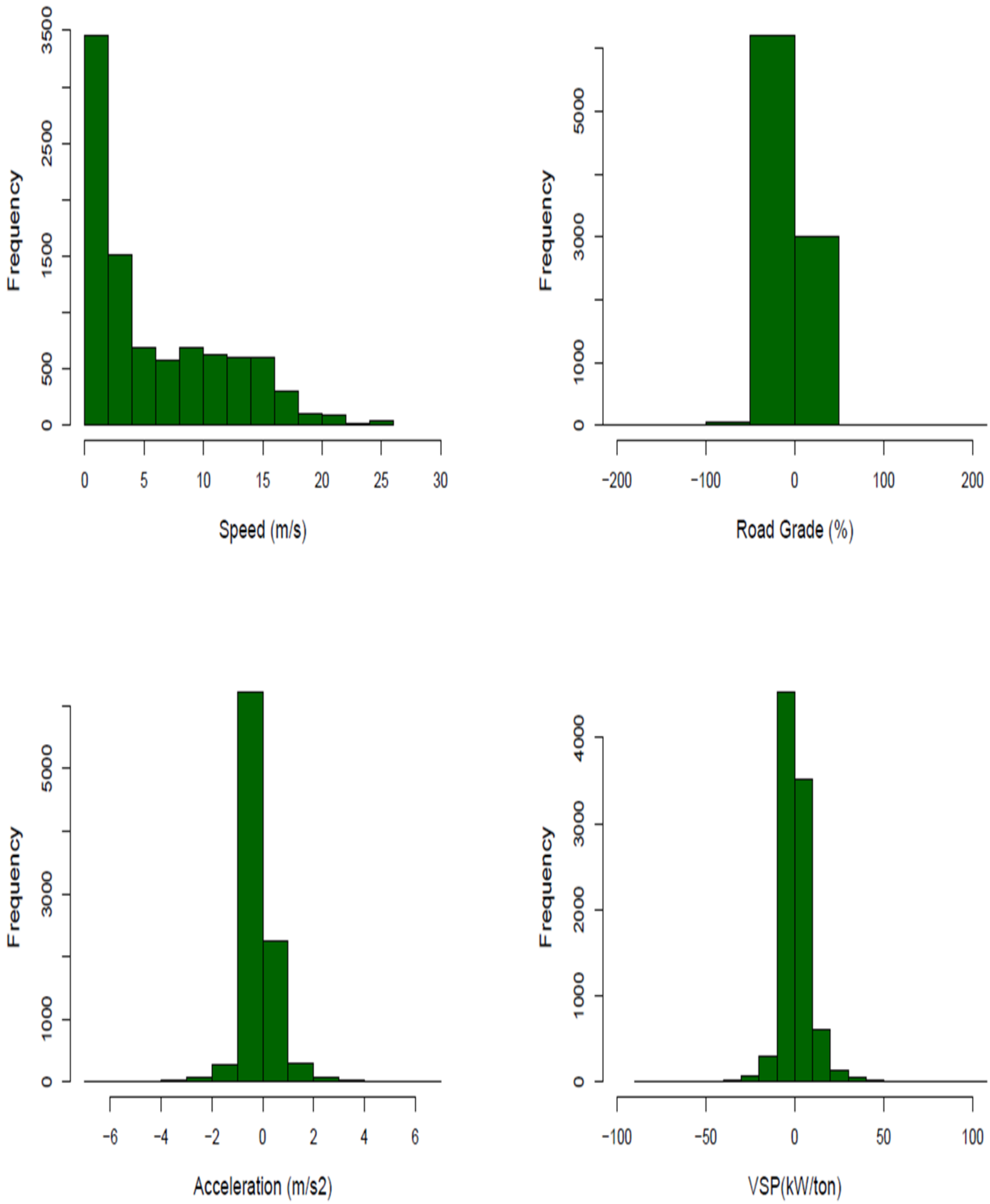


Figure S 30: Distribution of variables determining VSP and VSP for Test 11

VSP COMPARED TO SENSOR VOLTAGE BEFORE CORRELATION ALIGNMENT

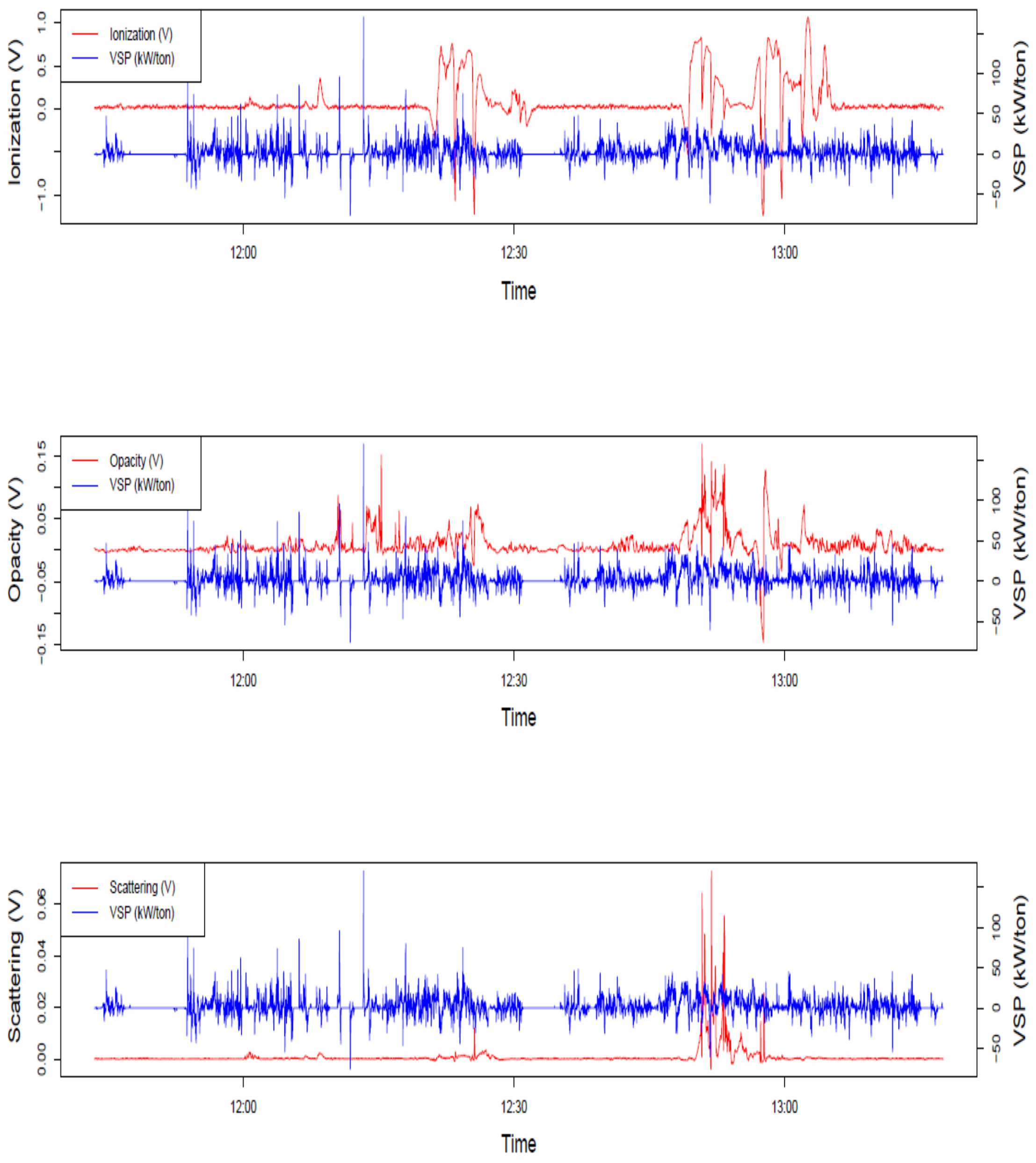


Figure S 31: VSP compared to sensor voltage (scattering, oinization, opacity) for Test 8

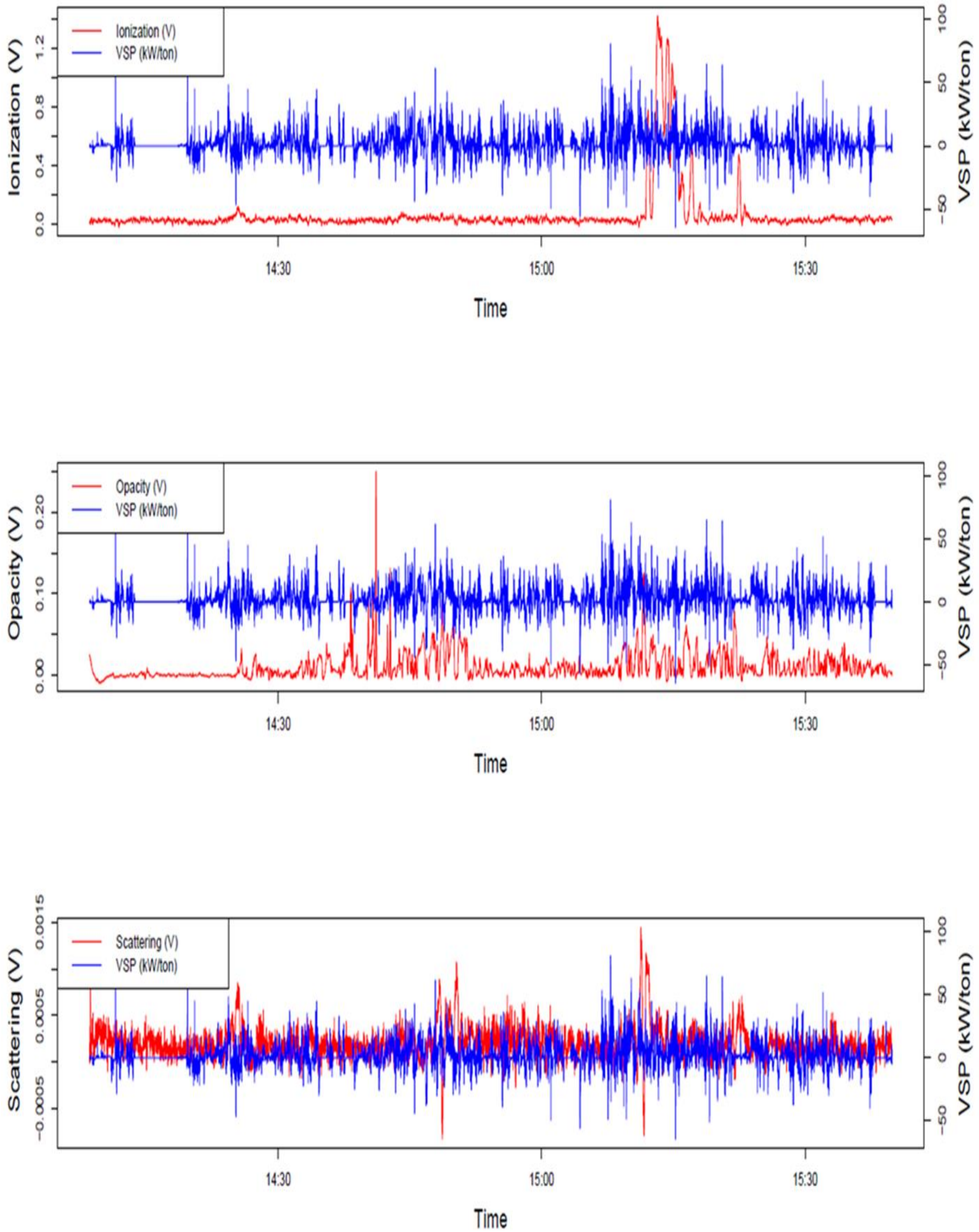


Figure S 32: VSP compared to sensor voltage (scattering, oinization, opacity) for Test 9

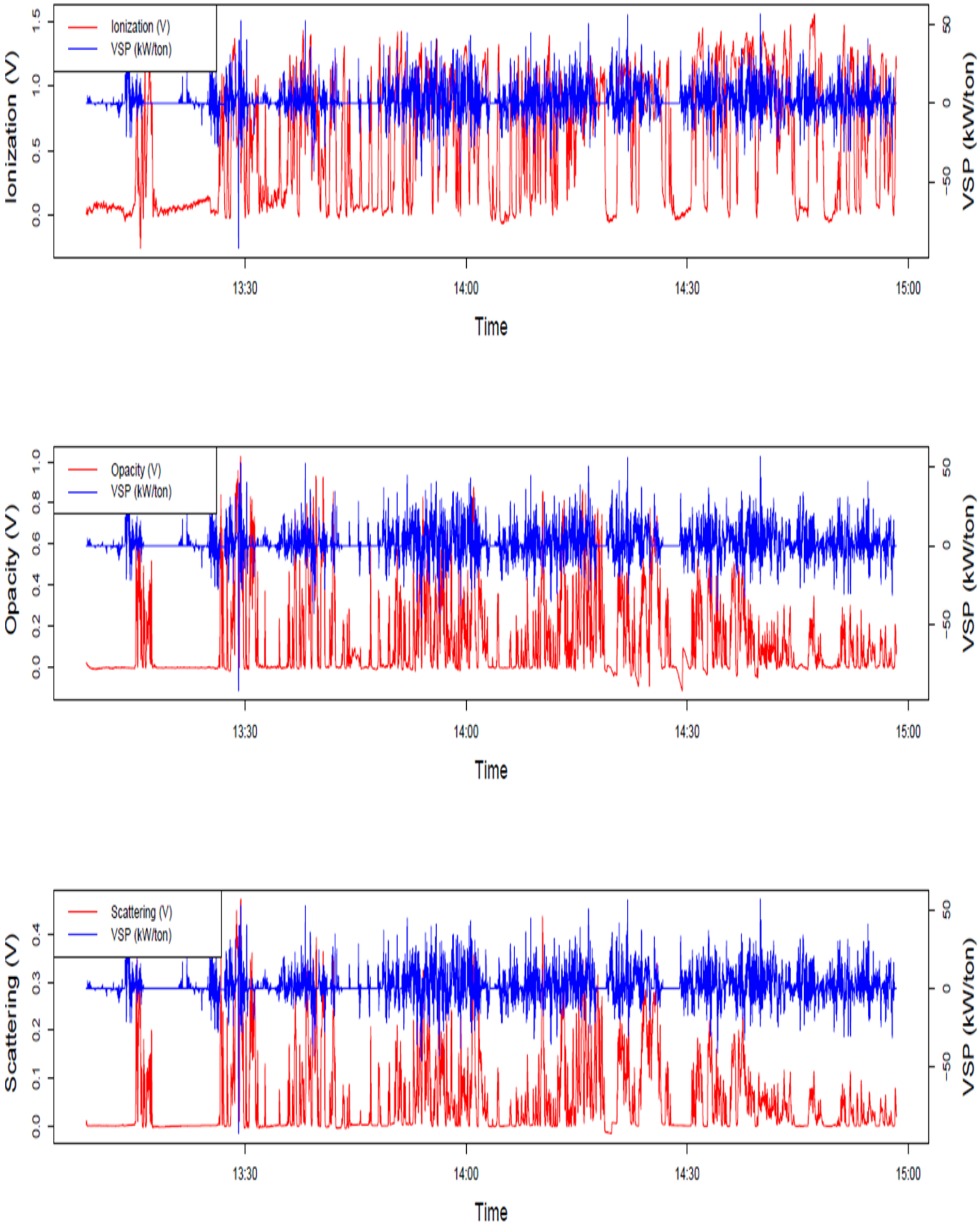


Figure S 33: VSP compared to sensor voltage (scattering, oinization, opacity) for Test 10

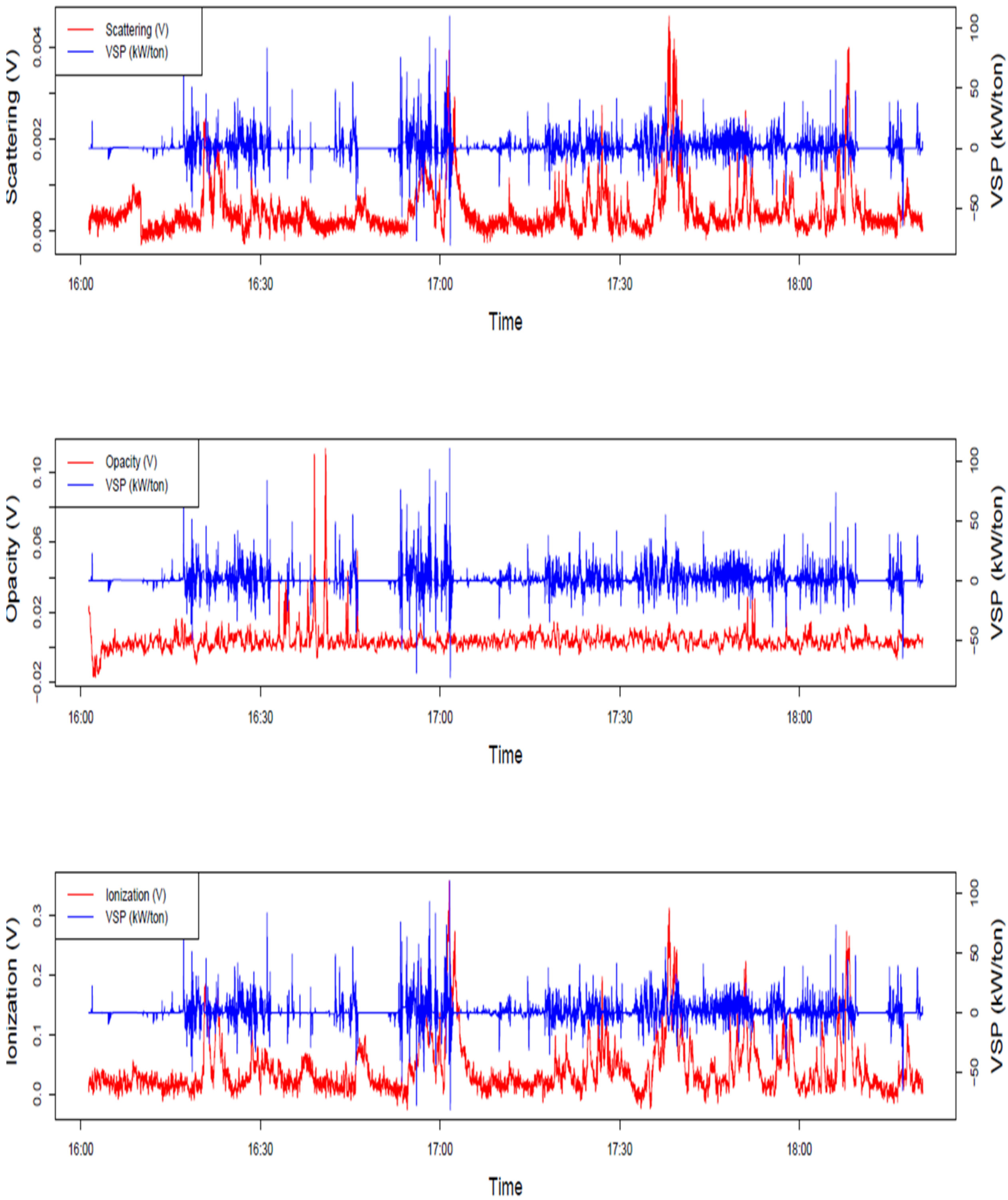


Figure S 34: VSP compared to sensor voltage (scattering, oinization, opacity) for Test 11

VSP BINS AND SENSOR VOLTAGE

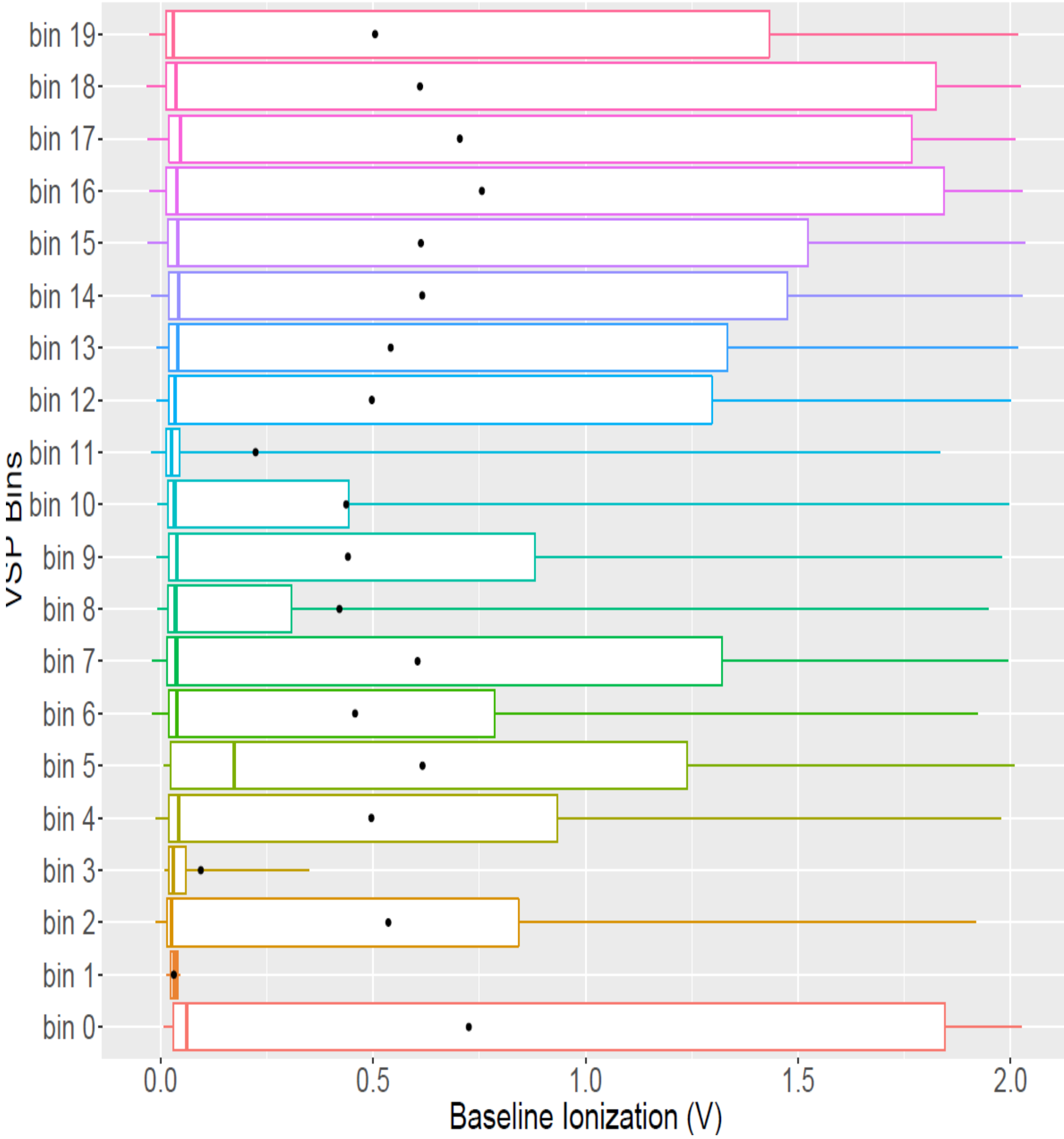


Figure S 35: VSP bins and baseline corrected ionization sensor voltage for Test 8

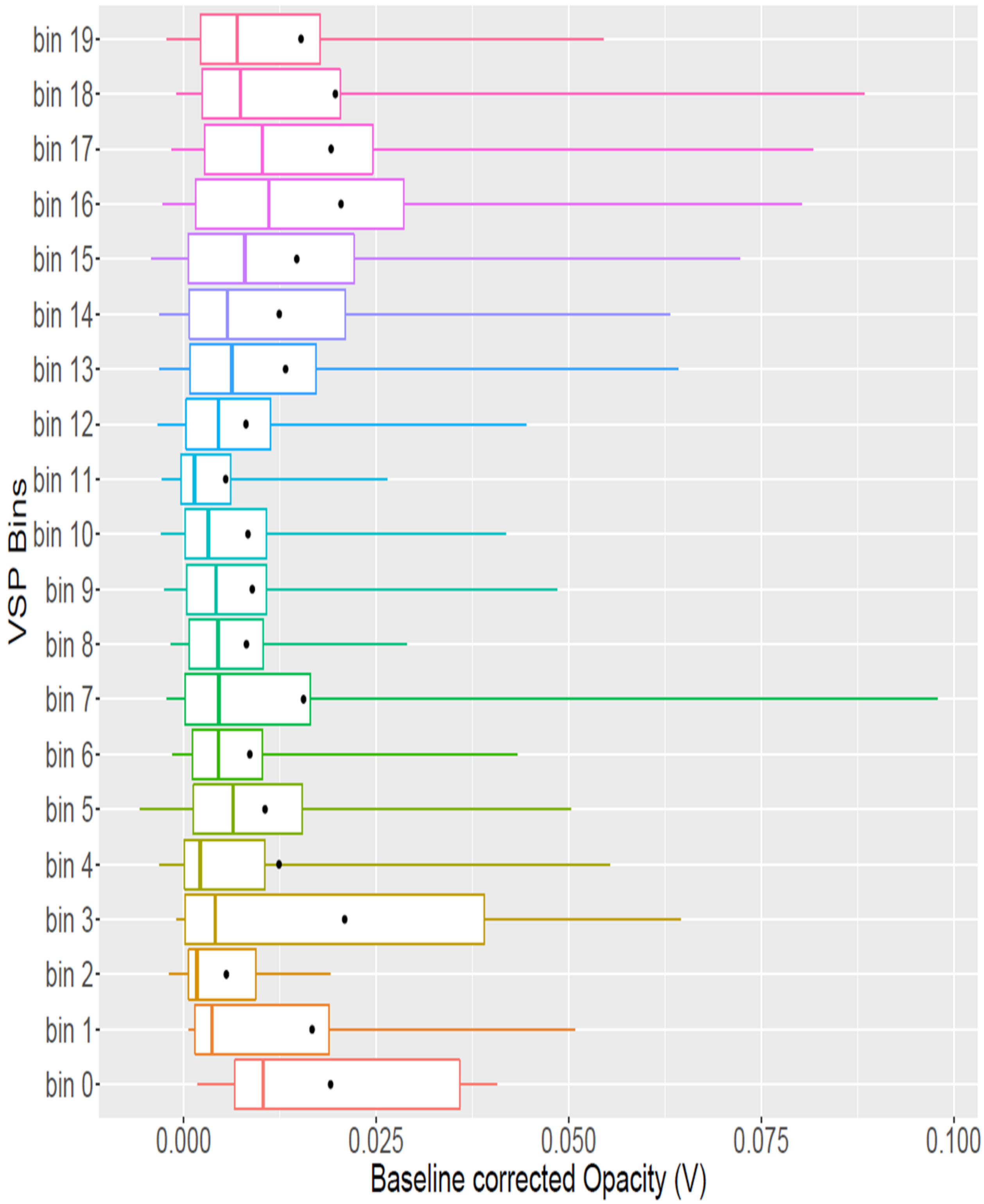


Figure S 36: VSP bins and baseline corrected opacity sensor voltage for Test 8

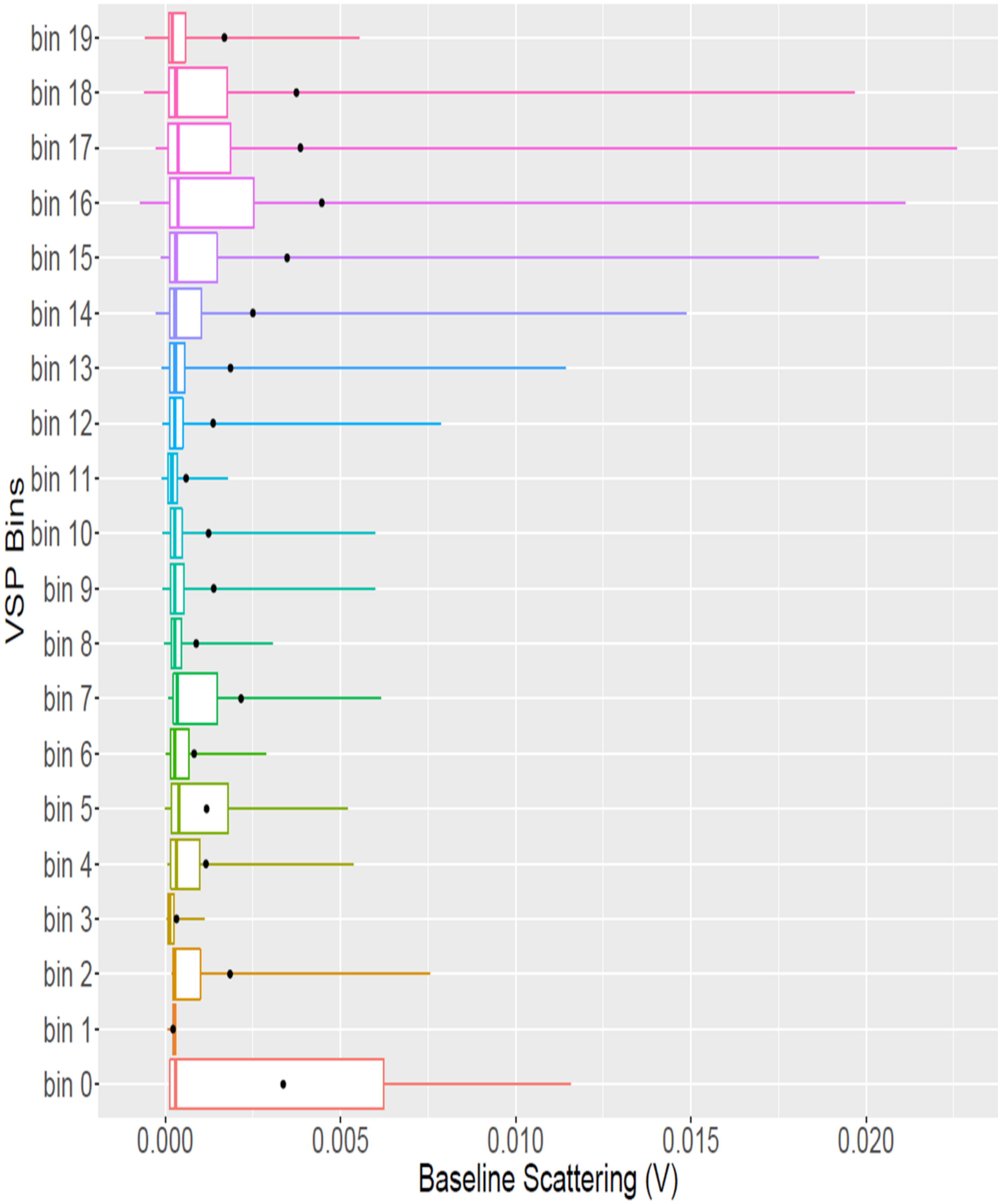


Figure S 37: VSP bins and baseline corrected scattering sensor voltage for Test 8

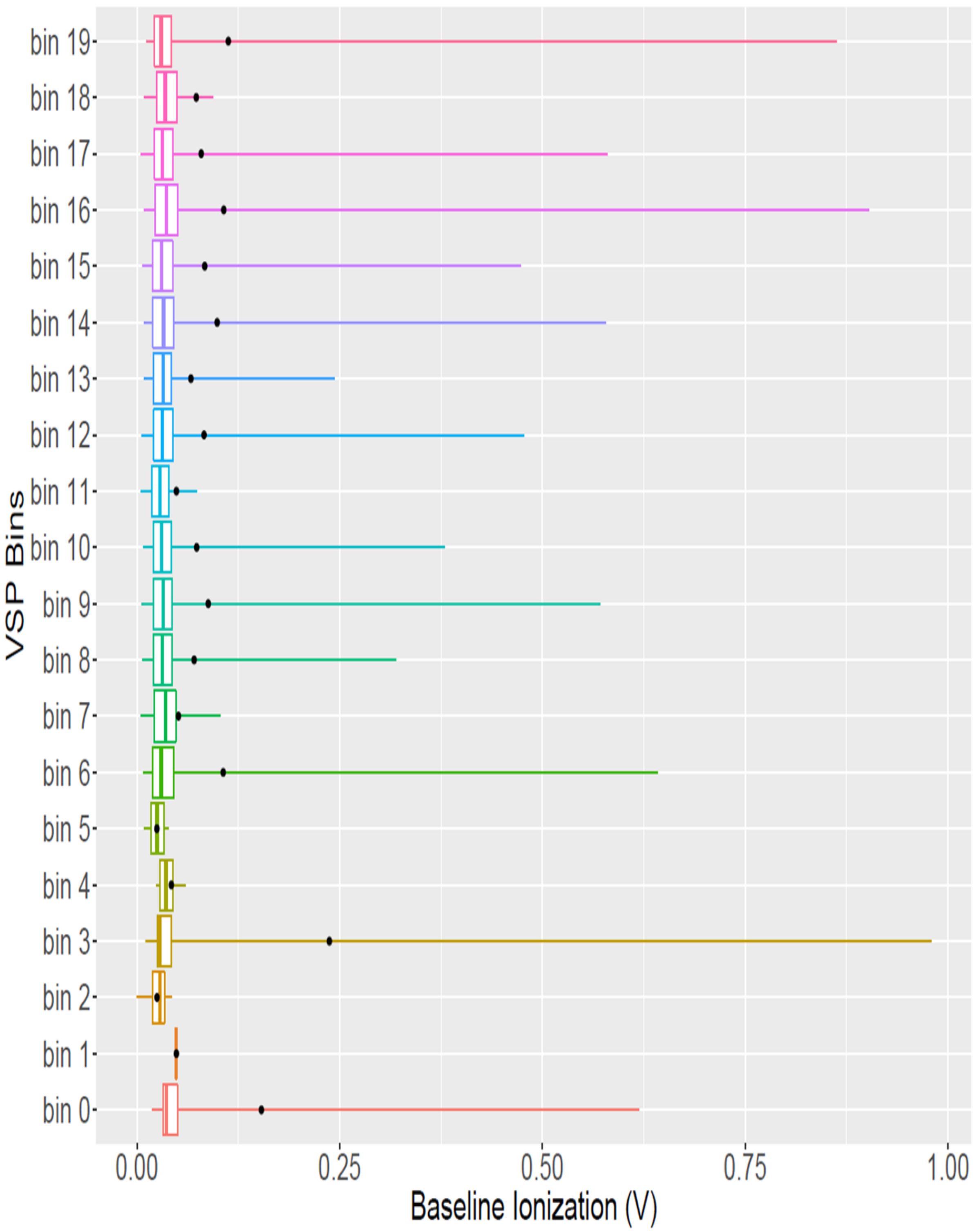


Figure S 38: VSP bins and baseline corrected ionization sensor voltage for Test 9

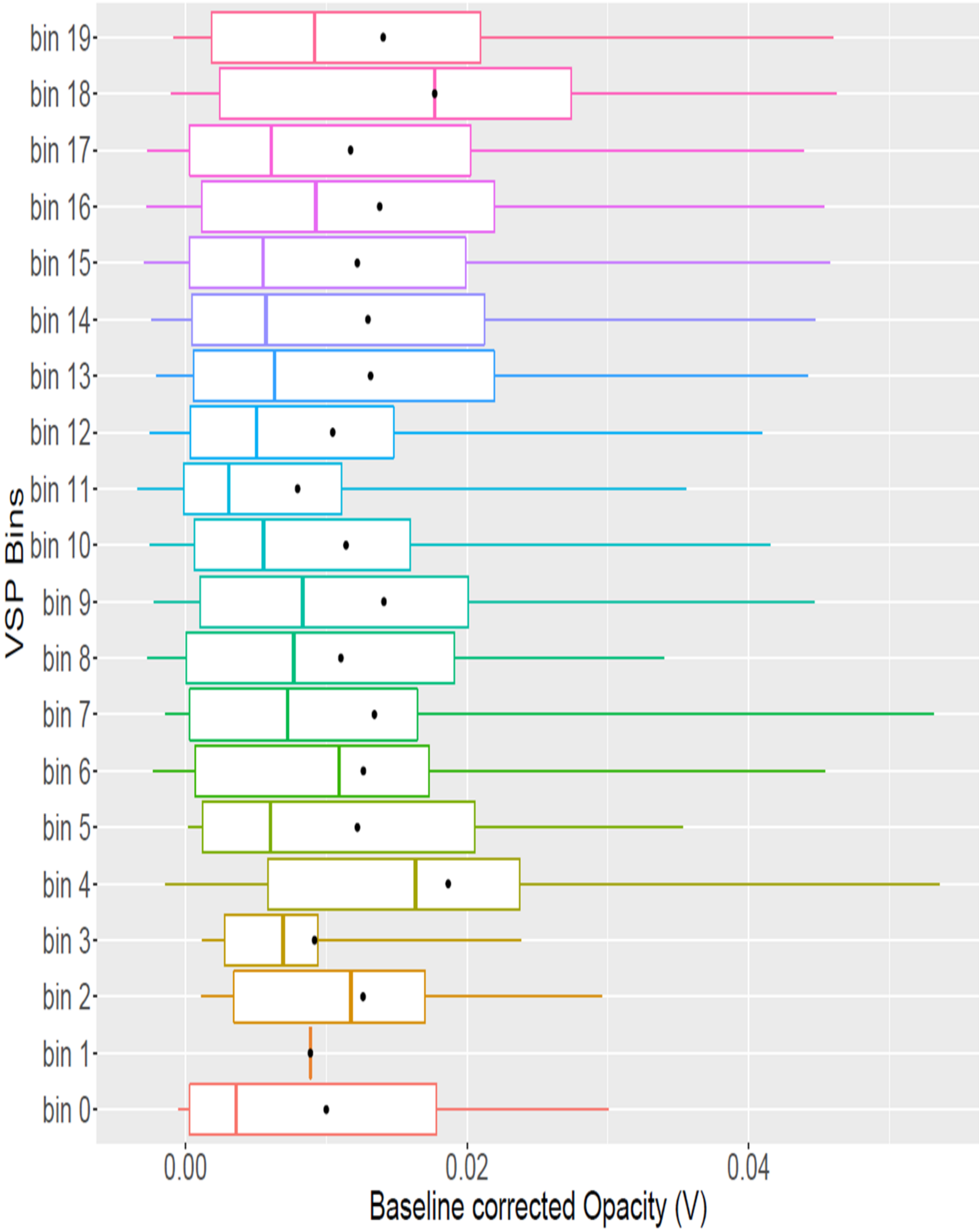


Figure S 39: VSP bins and baseline corrected opacity sensor voltage for Test 9

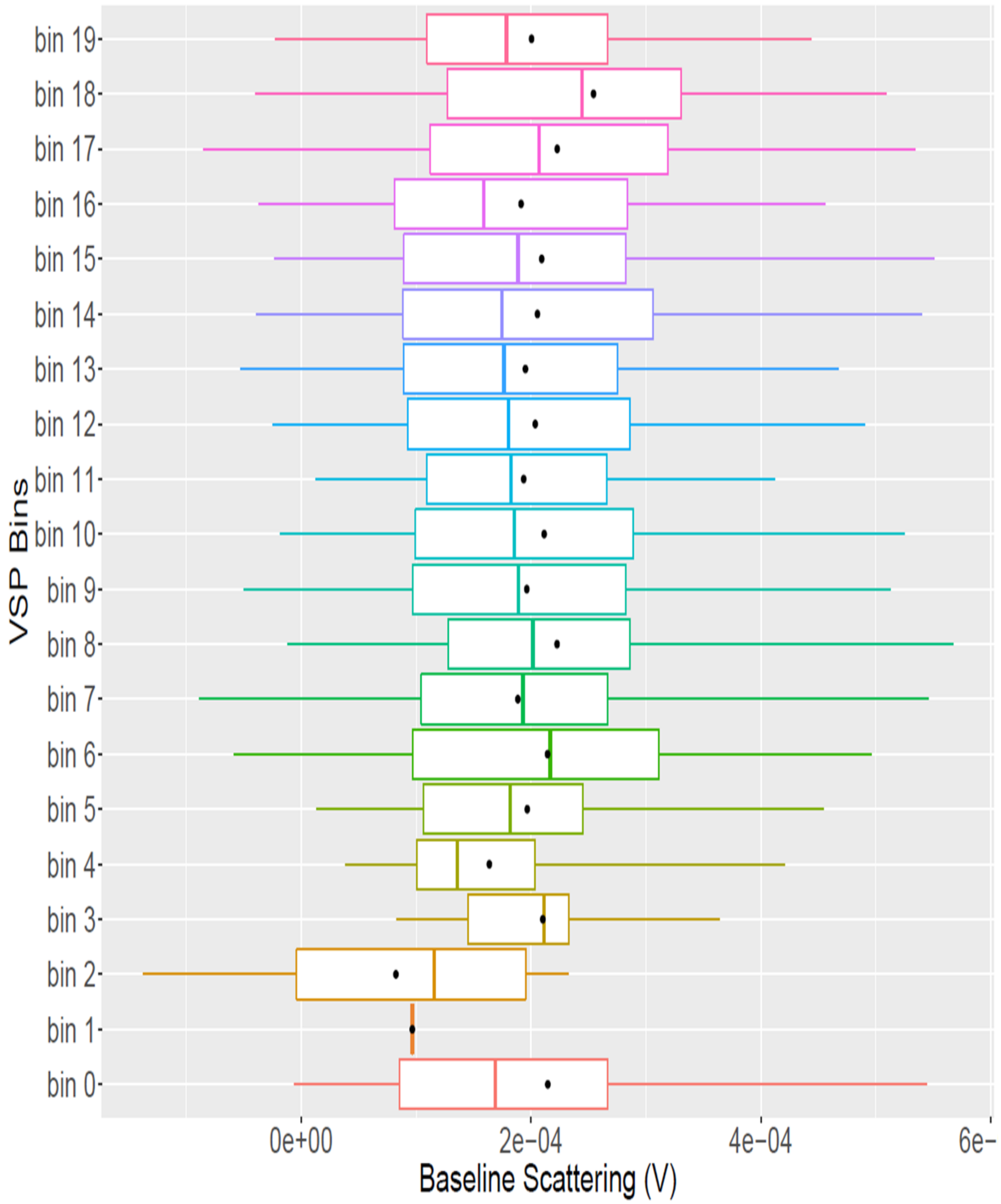


Figure S 40 : VSP bins and baseline corrected scattering sensor voltage for Test 9

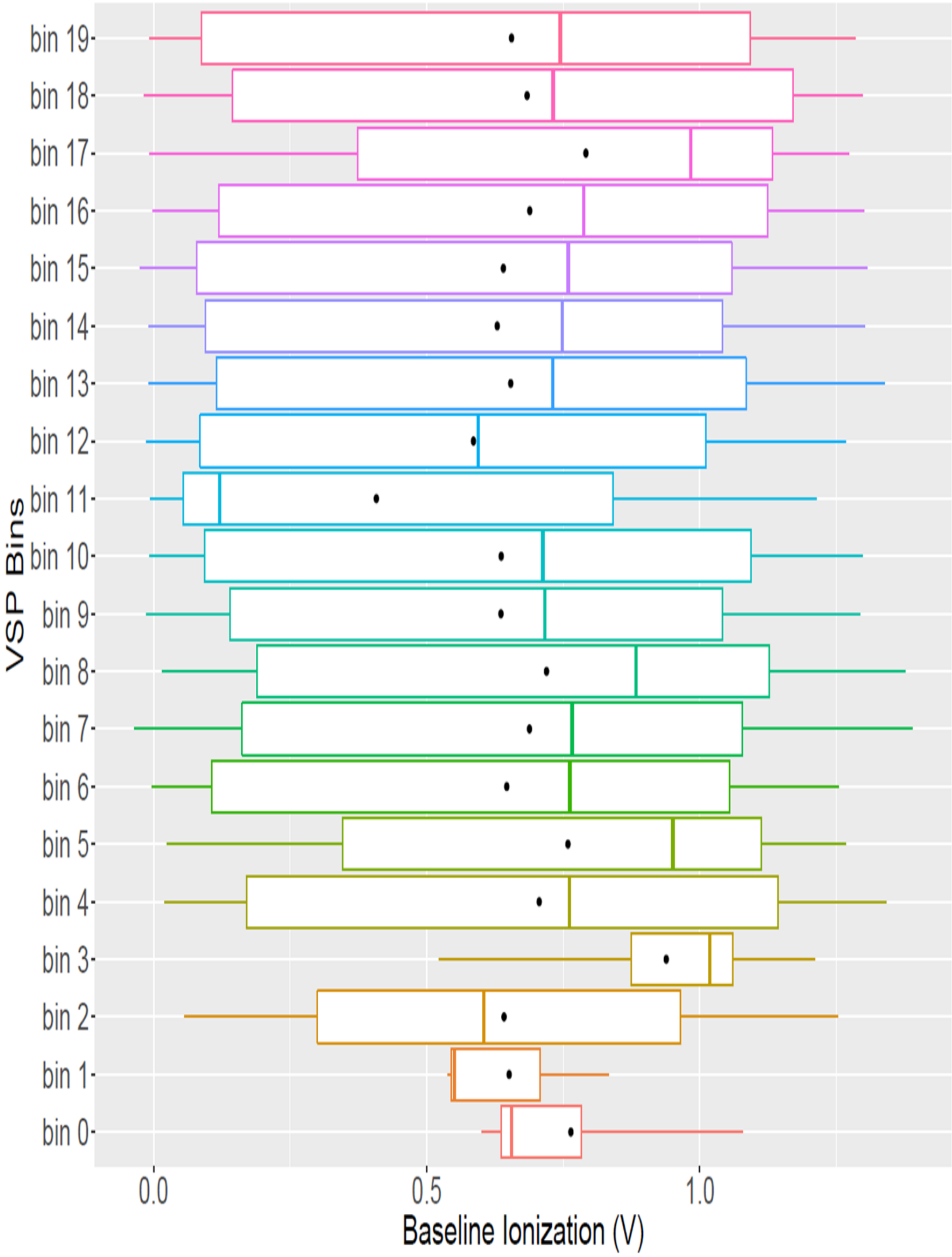


Figure S 41: VSP bins and baseline corrected ionization sensor voltage for Test 10

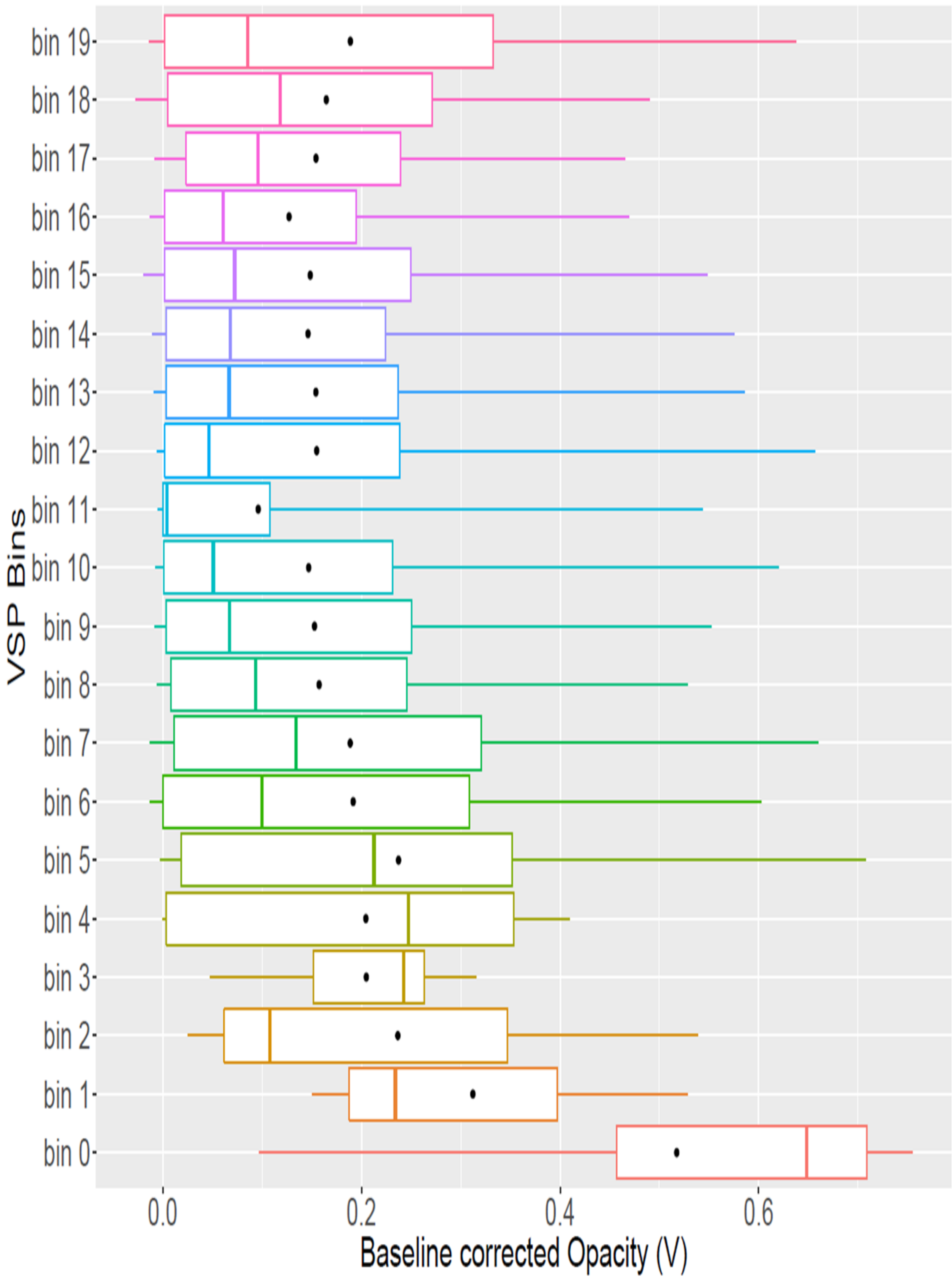
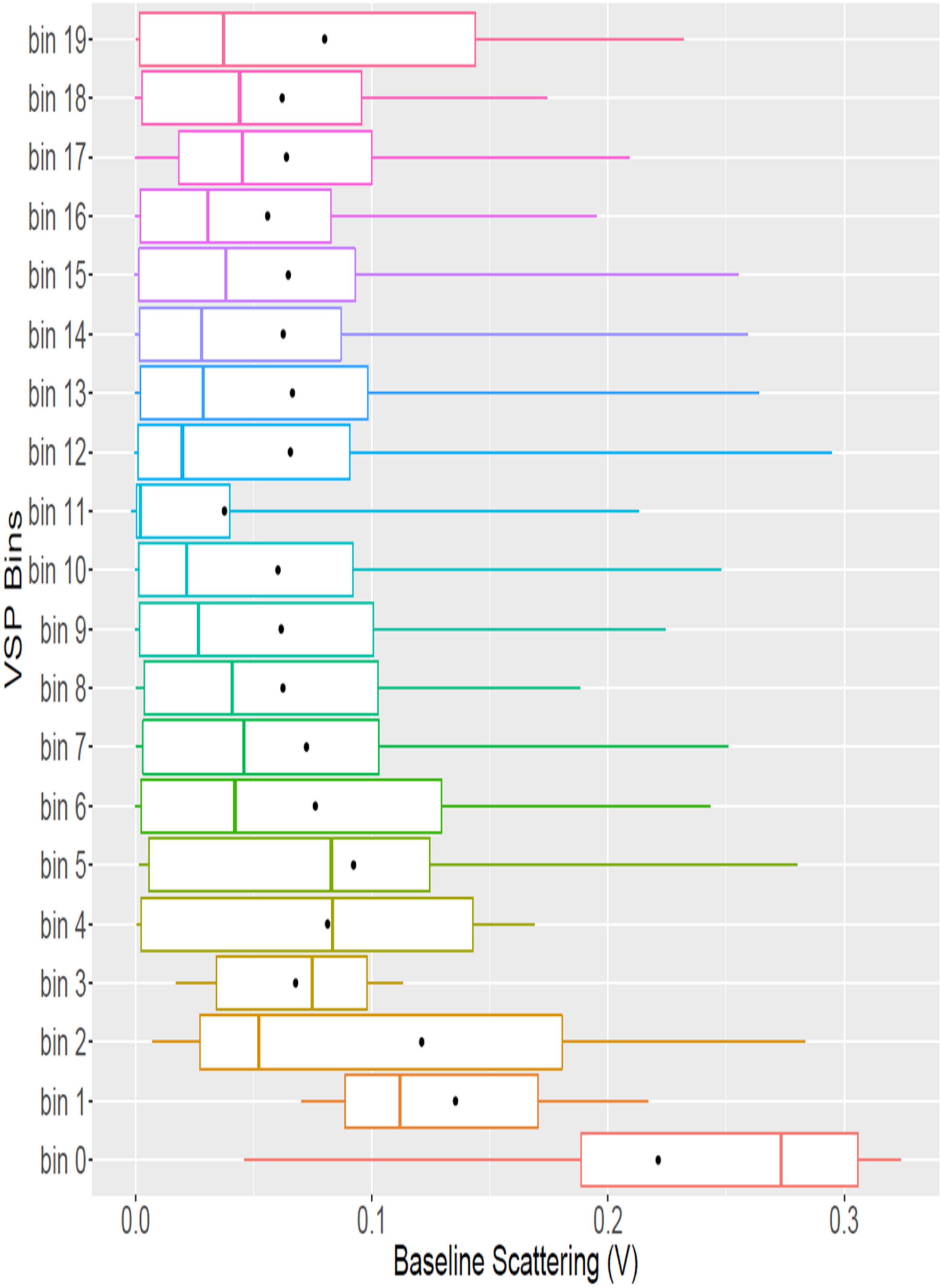


Figure S 42: VSP bins and baseline corrected opacity sensor voltage for Test 10



S 43 : VSP bins and baseline corrected scattering sensor voltage for Test 10

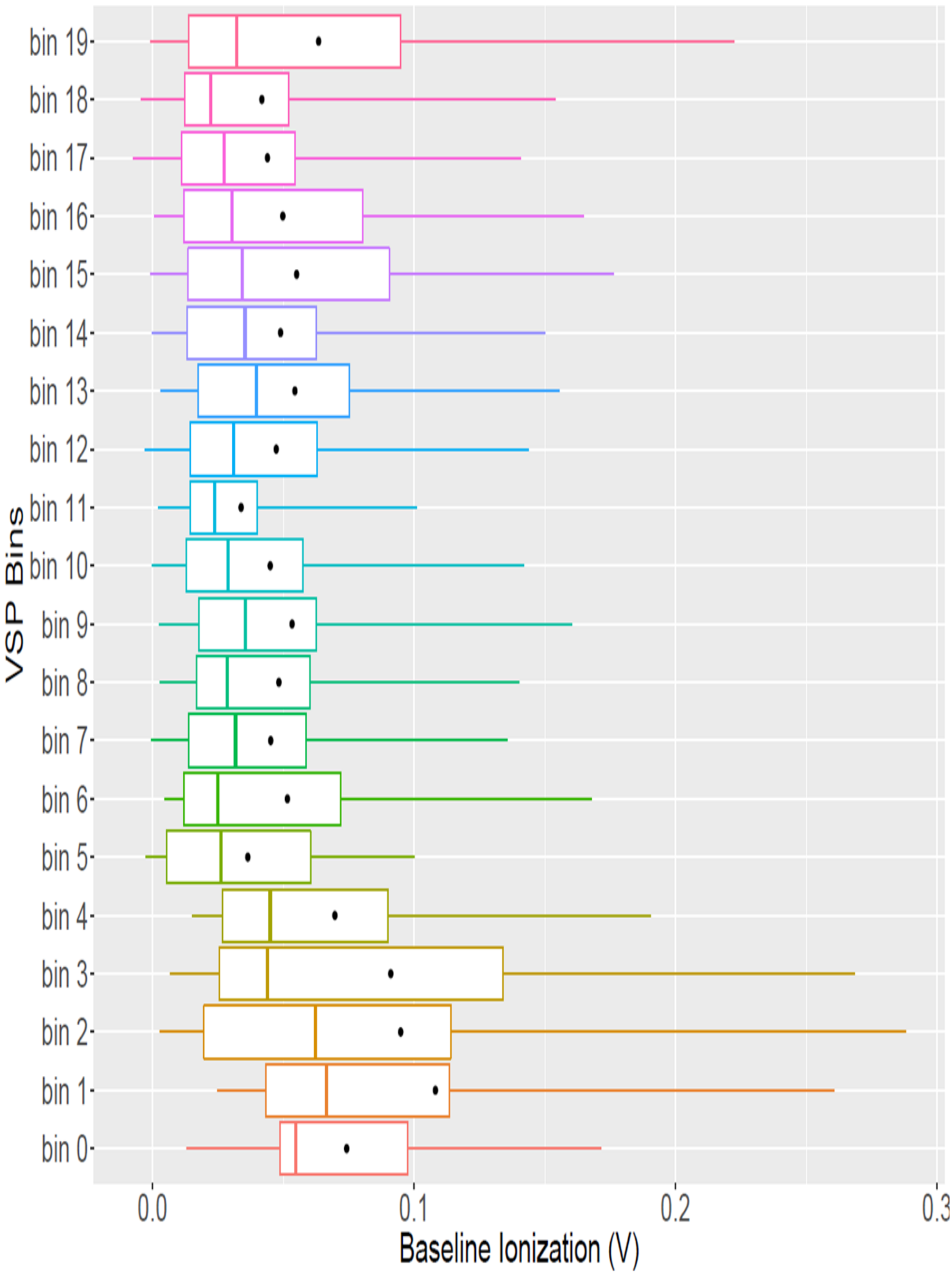


Figure S 44: VSP bins and baseline corrected ionization sensor voltage for Test 11

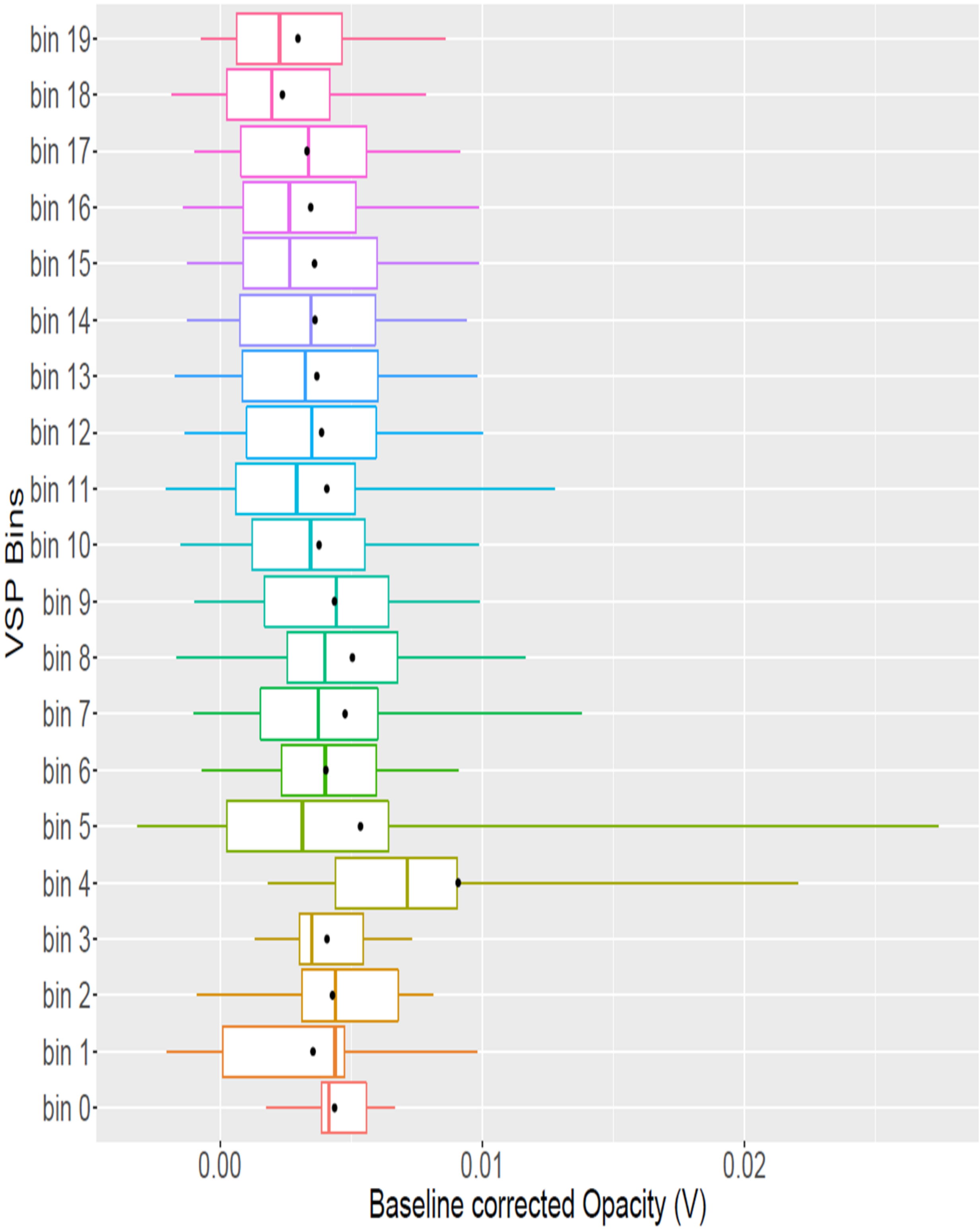


Figure S 45 : VSP bins and baseline corrected opacity sensor voltage for Test 11

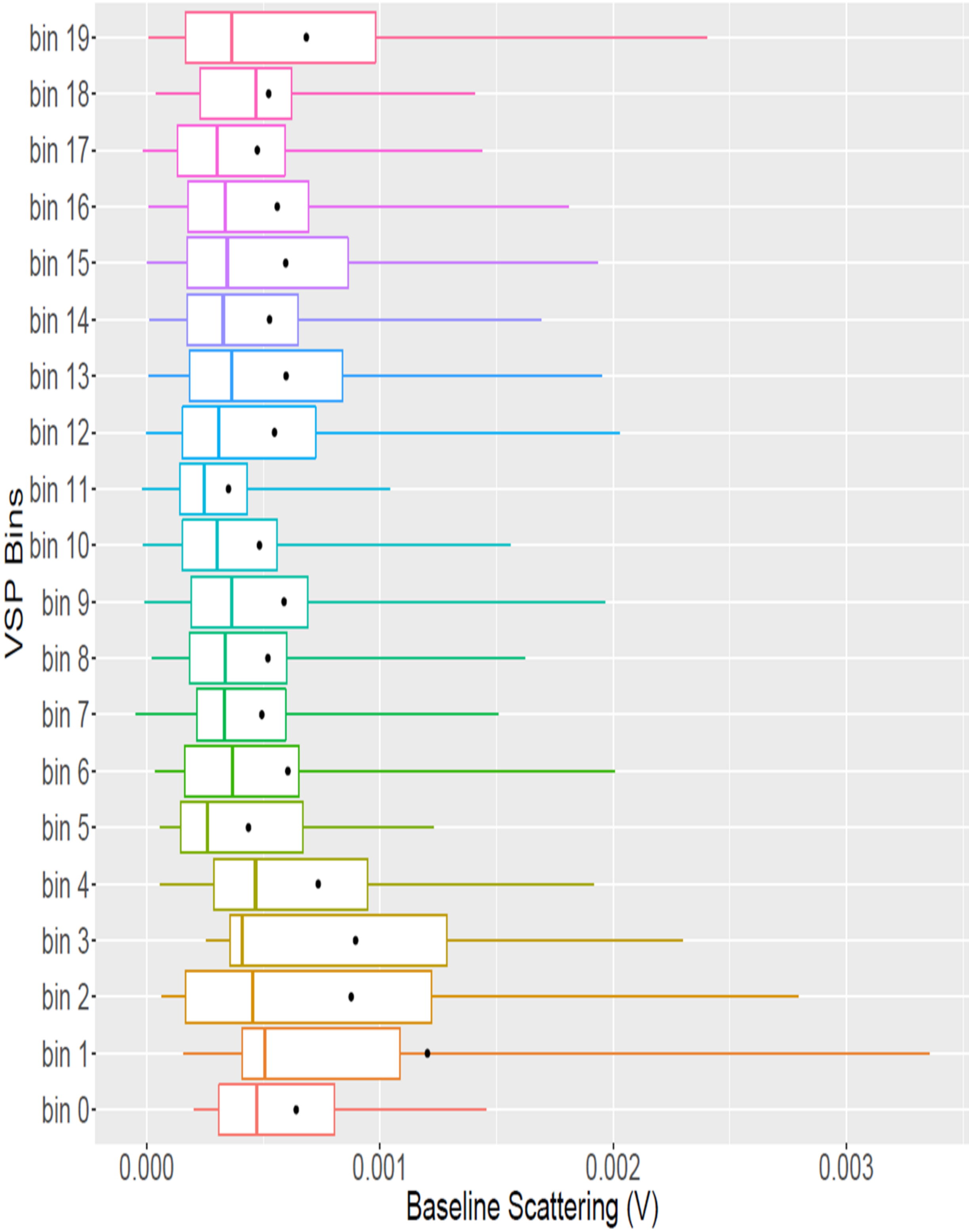


Figure S 46: VSP bins and baseline corrected scattering sensor voltage for Test 11

3D SCATTER PLOT AND PARAMETERS

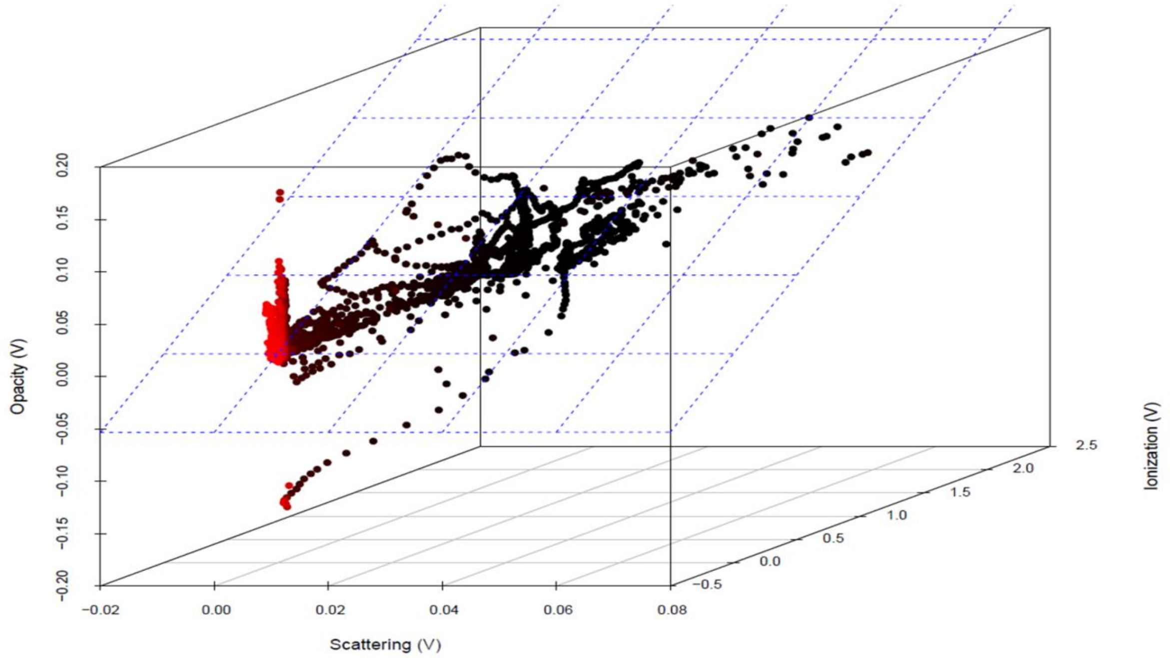


Figure S 47: 3D scatter plot of the three sensors (opacity, scattering and ionization) sensor voltage with a linear regression plane for Test 8

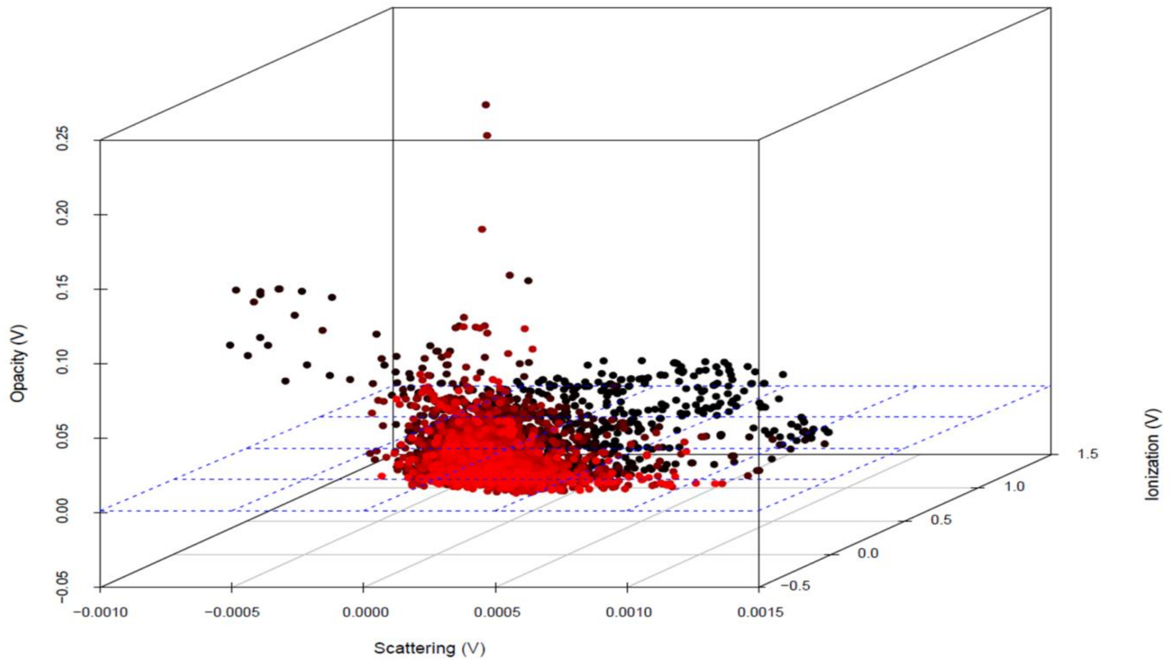


Figure S 48: 3D scatter plot of the three sensors (opacity, scattering and ionization) sensor voltage with a linear regression plane for Test 9

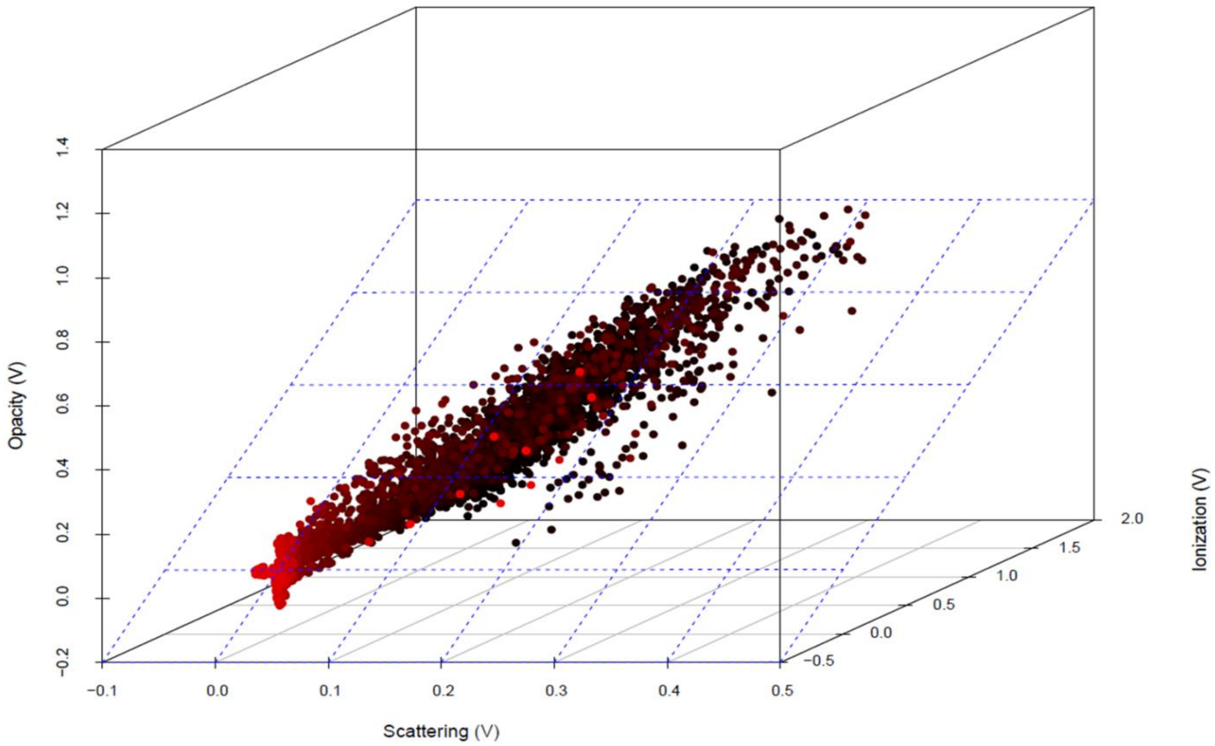


Figure S 49: 3D scatter plot of the three sensors (opacity, scattering and ionization) sensor voltage with a linear regression plane for Test 10

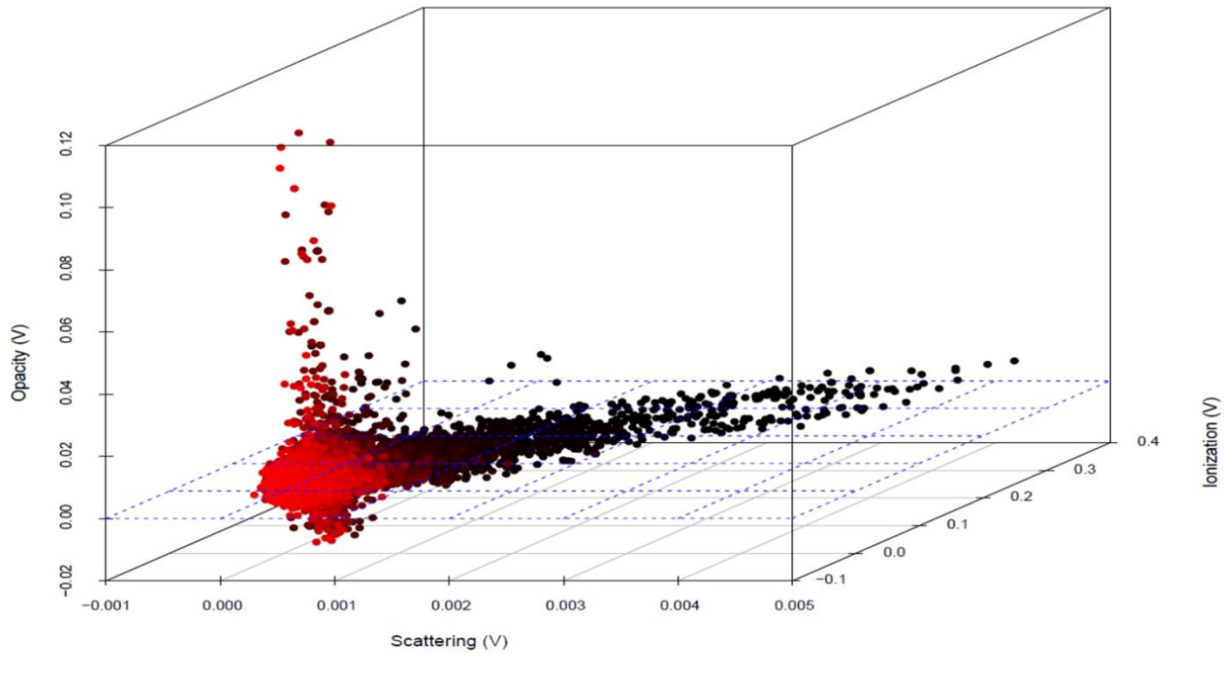


Figure S 50: 3D scatter plot of the three sensors (opacity, scattering and ionization) sensor voltage with a linear regression plane for Test 11

TEMPORAL AND SPATIAL MAPS OF SENSOR VOLTAGE

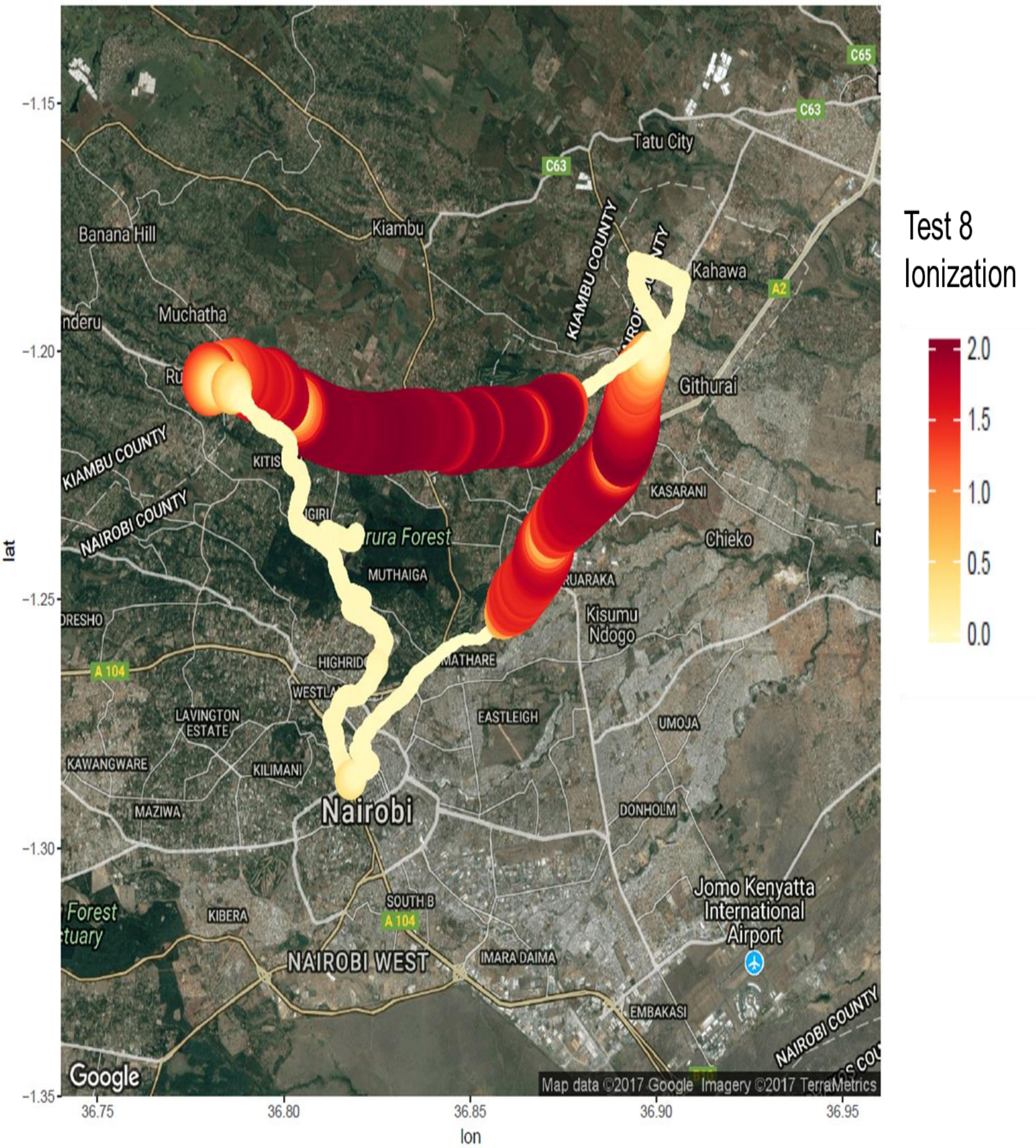


Figure S 51:Temporal and spatial map of ionization sensor voltage for Test 8

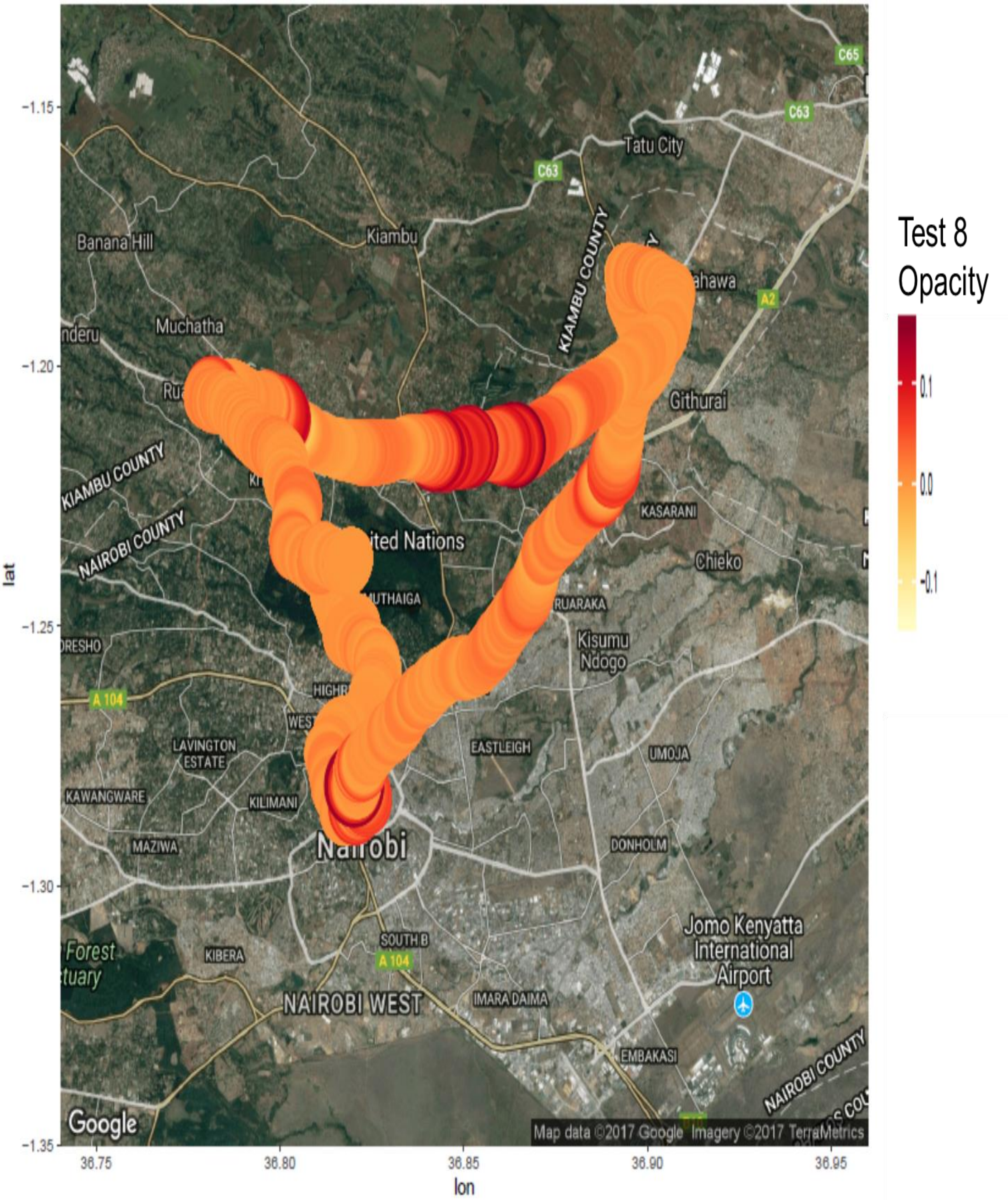


Figure S 52:Temporal and spatial map of opacity sensor voltage for Test 8

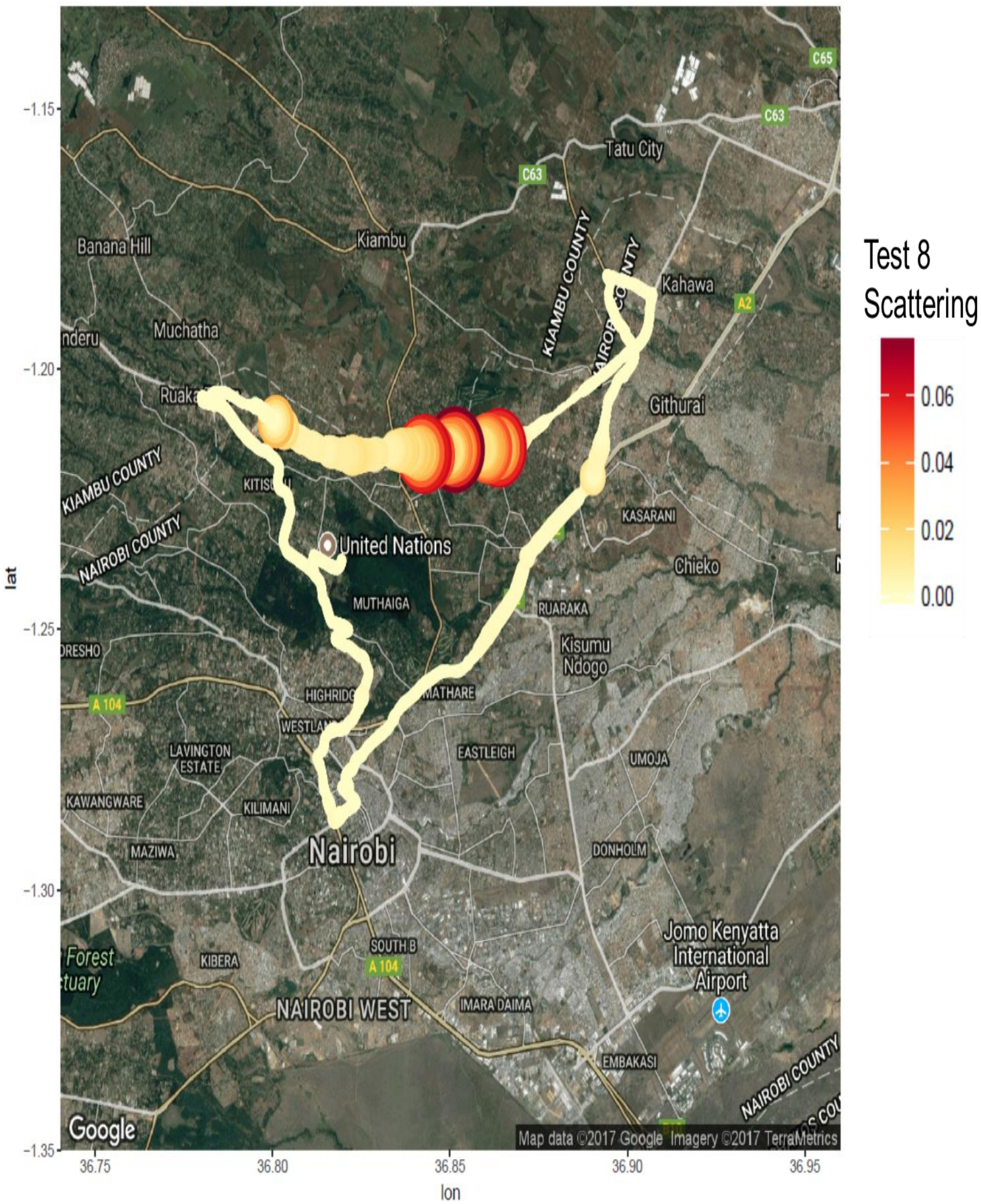


Figure S 53: Temporal and spatial map of scattering sensor voltage for Test 8

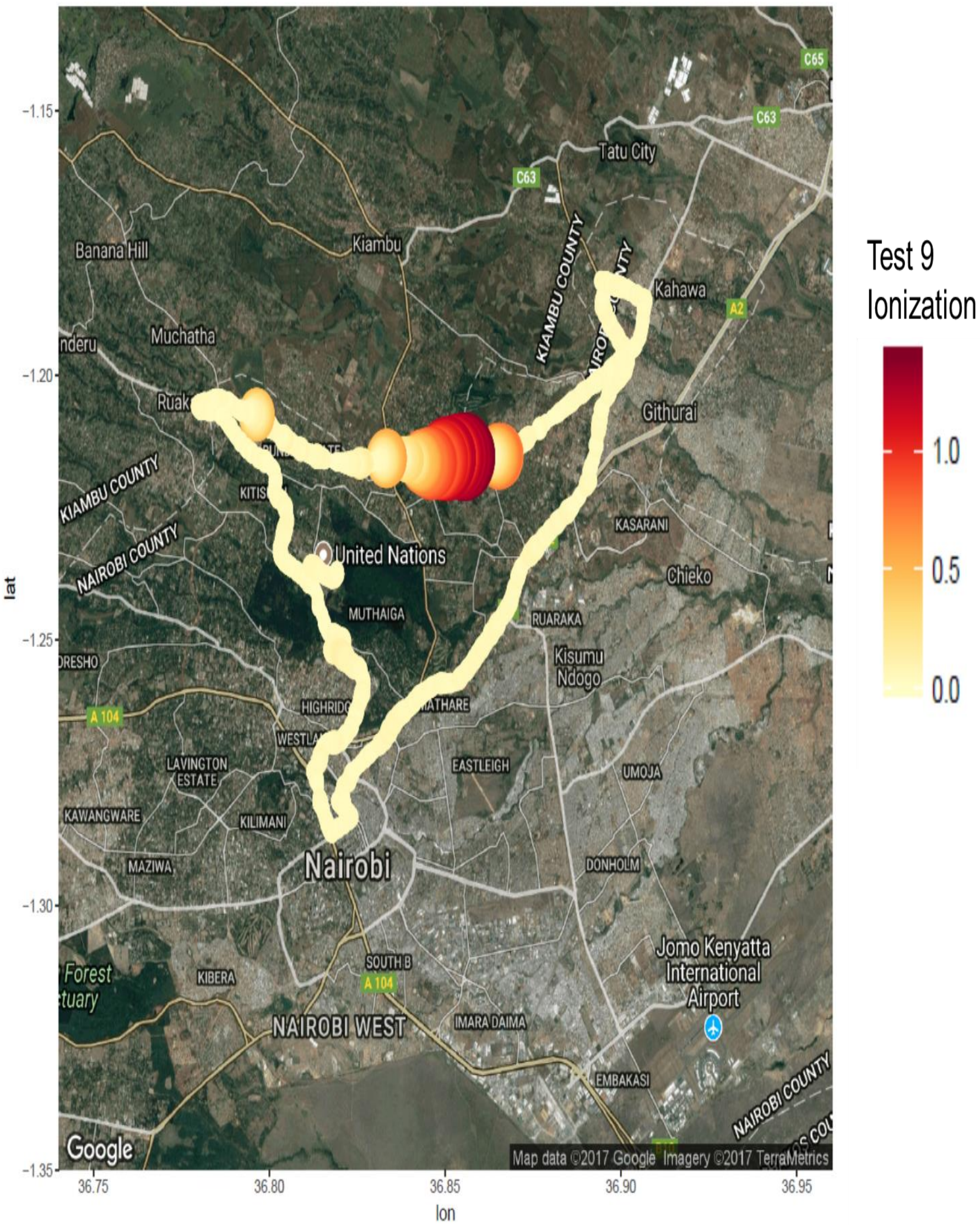
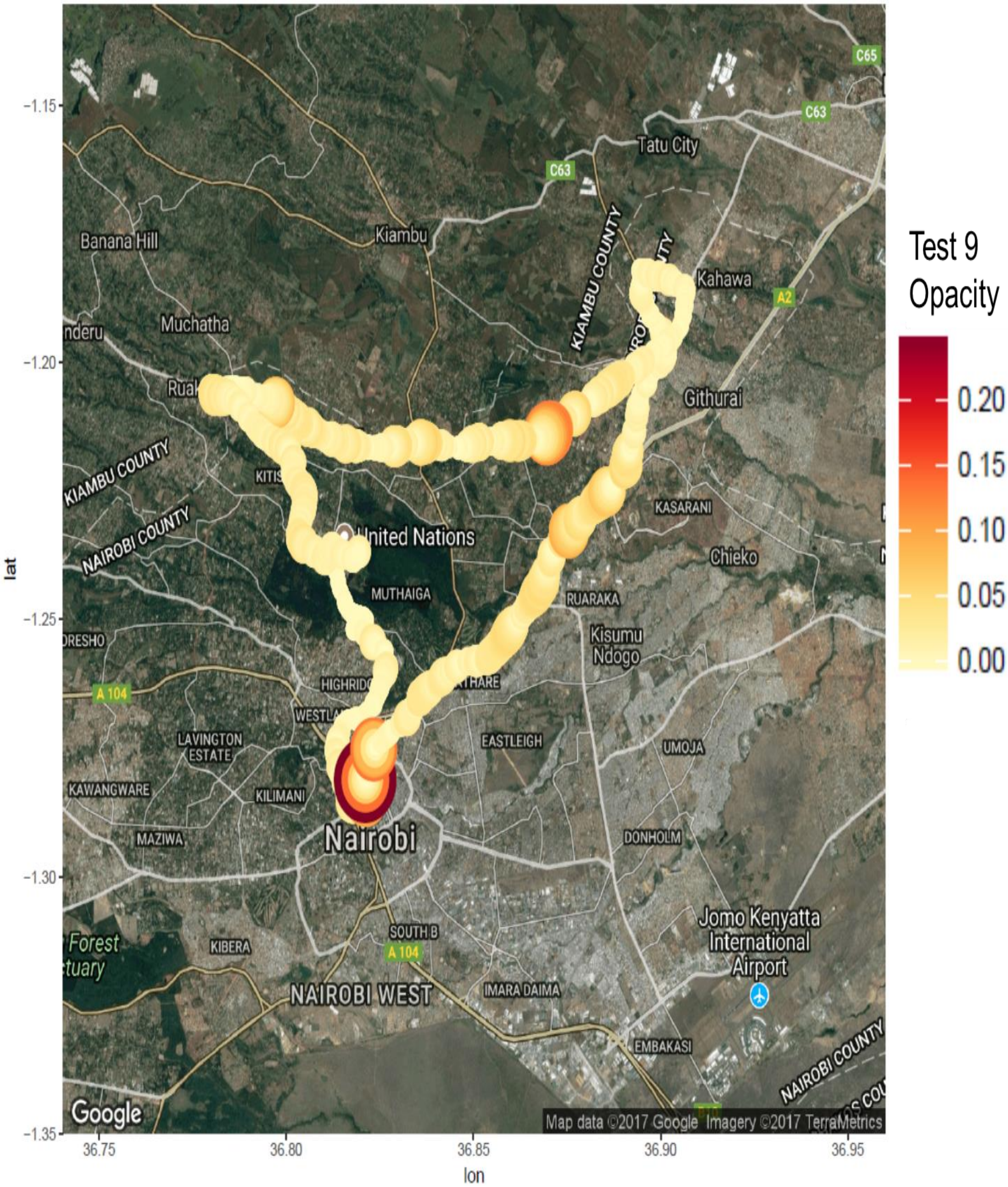


Figure S 54: Temporal and spatial map of ionization sensor voltage for Test 9



FigureS 55: Temporal and spatial map of opacity sensor voltage for Test 9

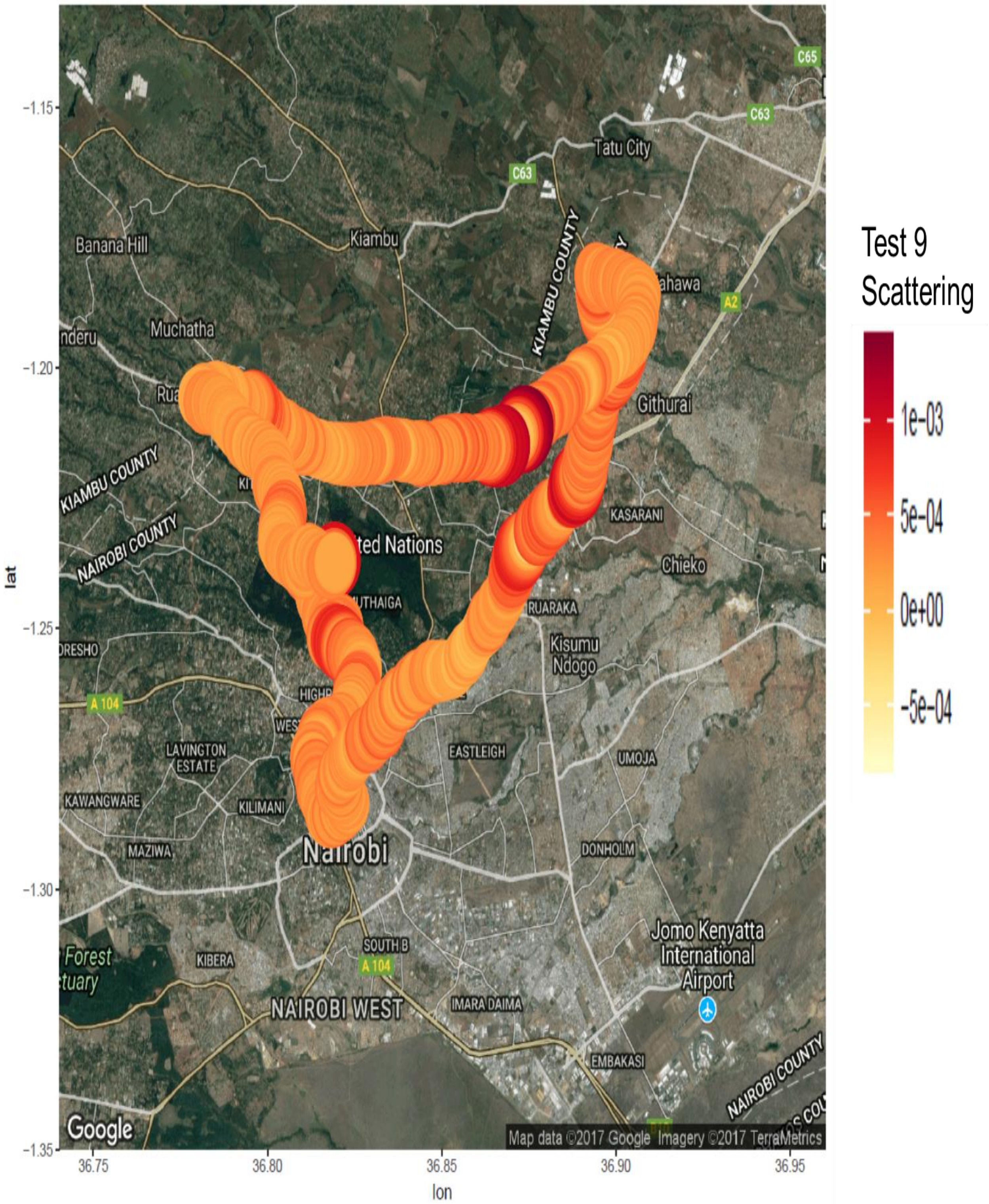


Figure S 56: Temporal and spatial map of scattering sensor voltage for Test 9

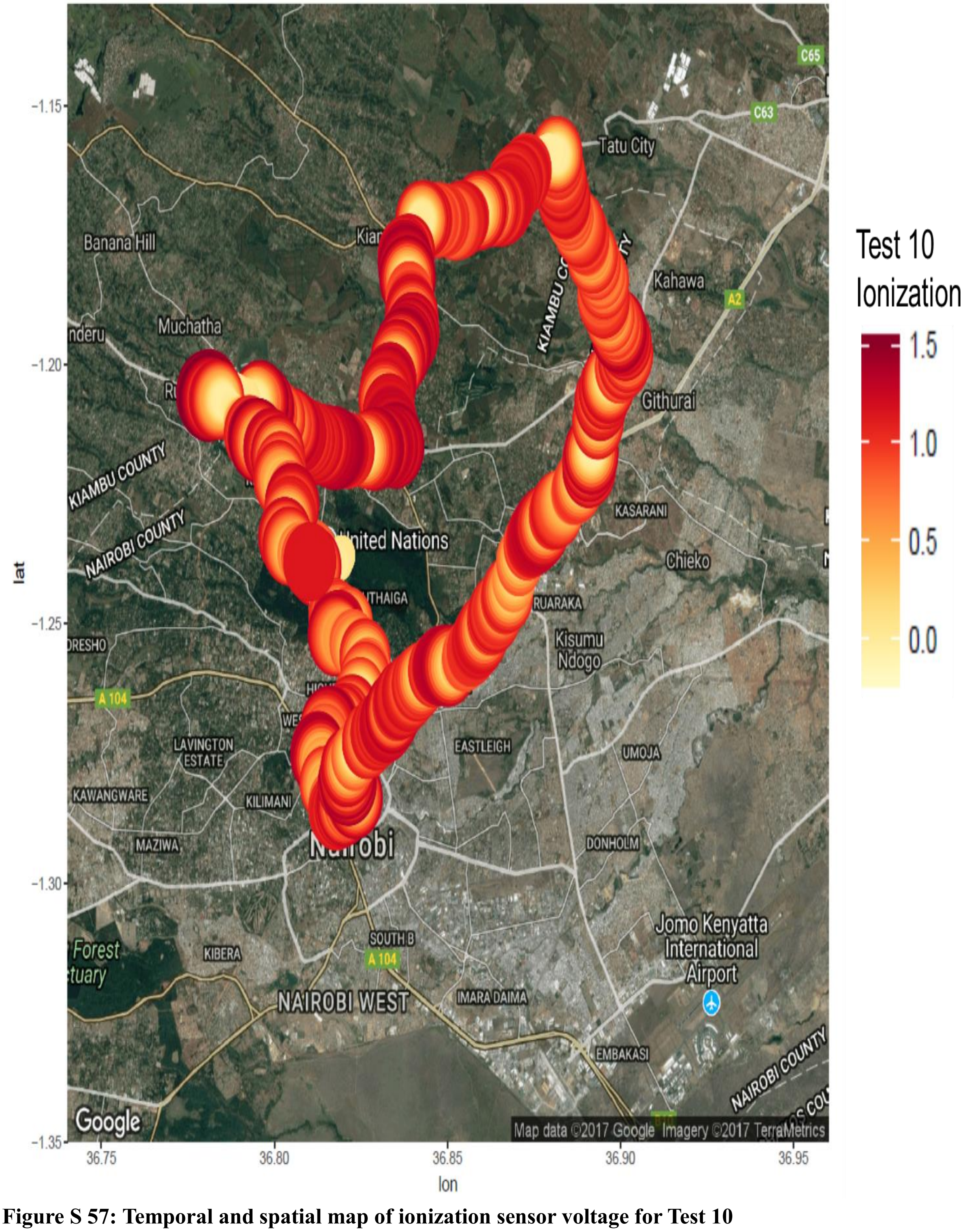


Figure S 57: Temporal and spatial map of ionization sensor voltage for Test 10

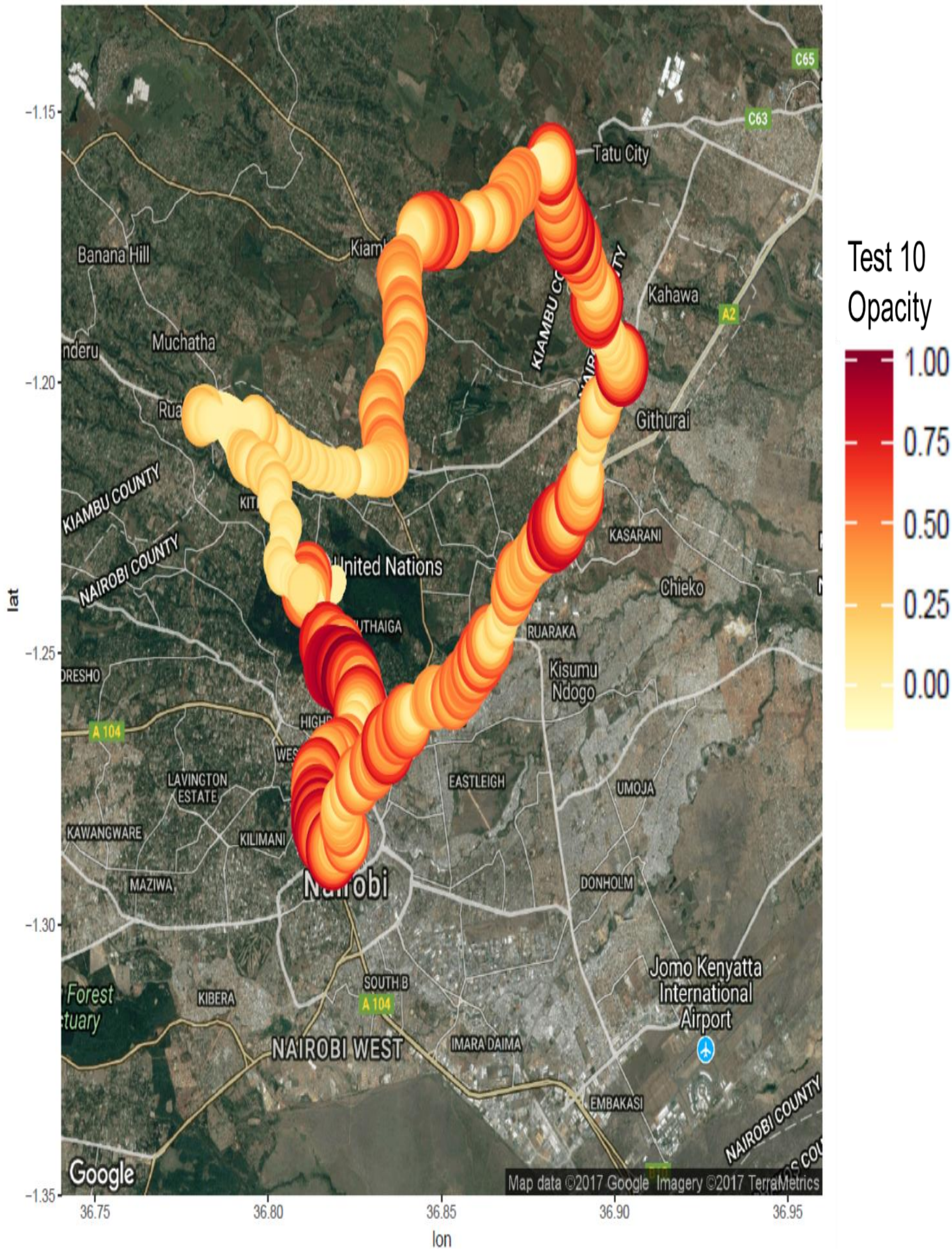


Figure S 58: Temporal and spatial map of opacity sensor voltage for Test 10

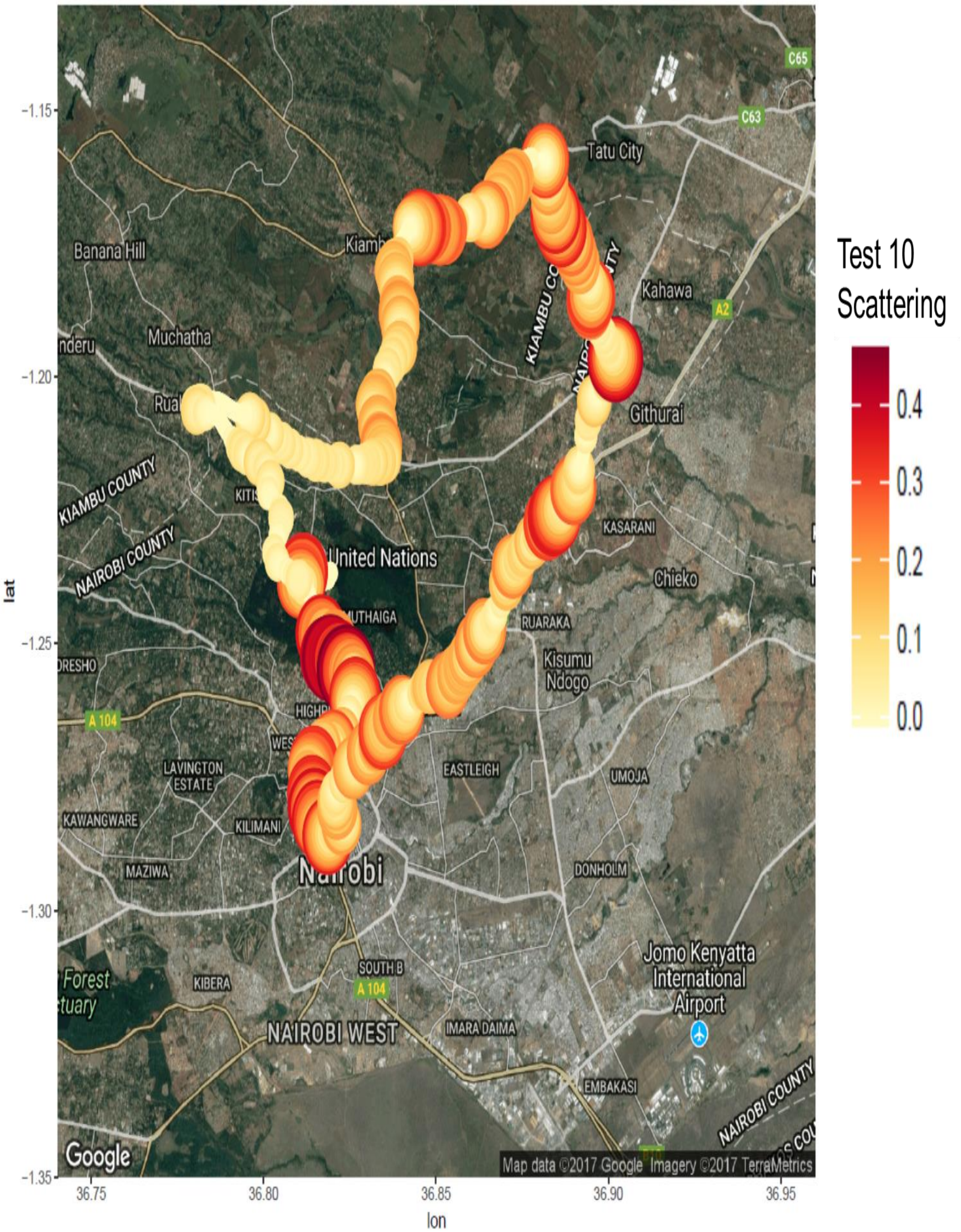


Figure S 59: Temporal and spatial map of scattering sensor voltage for Test 10

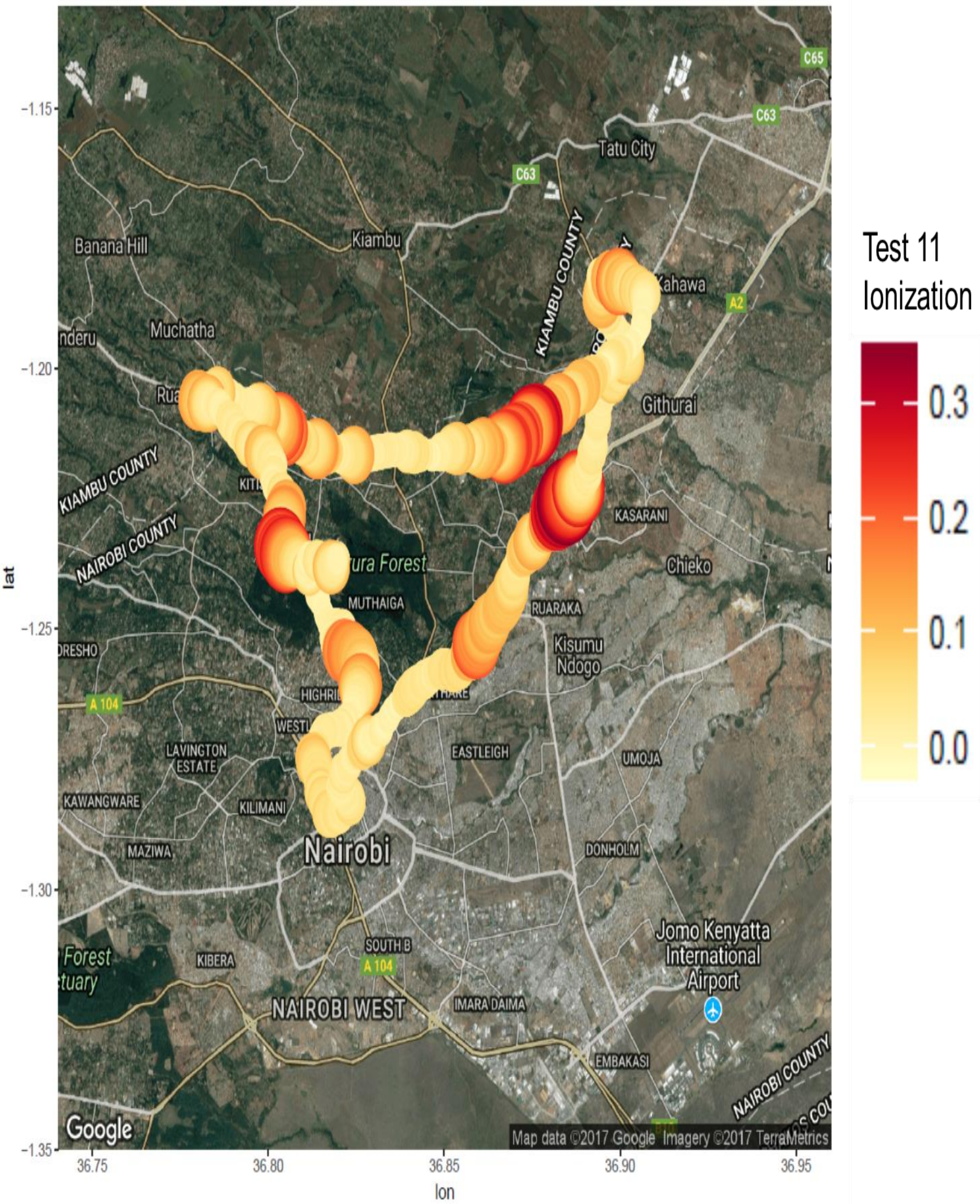


Figure S 60: Temporal and spatial map for ionization sensor for Test 11

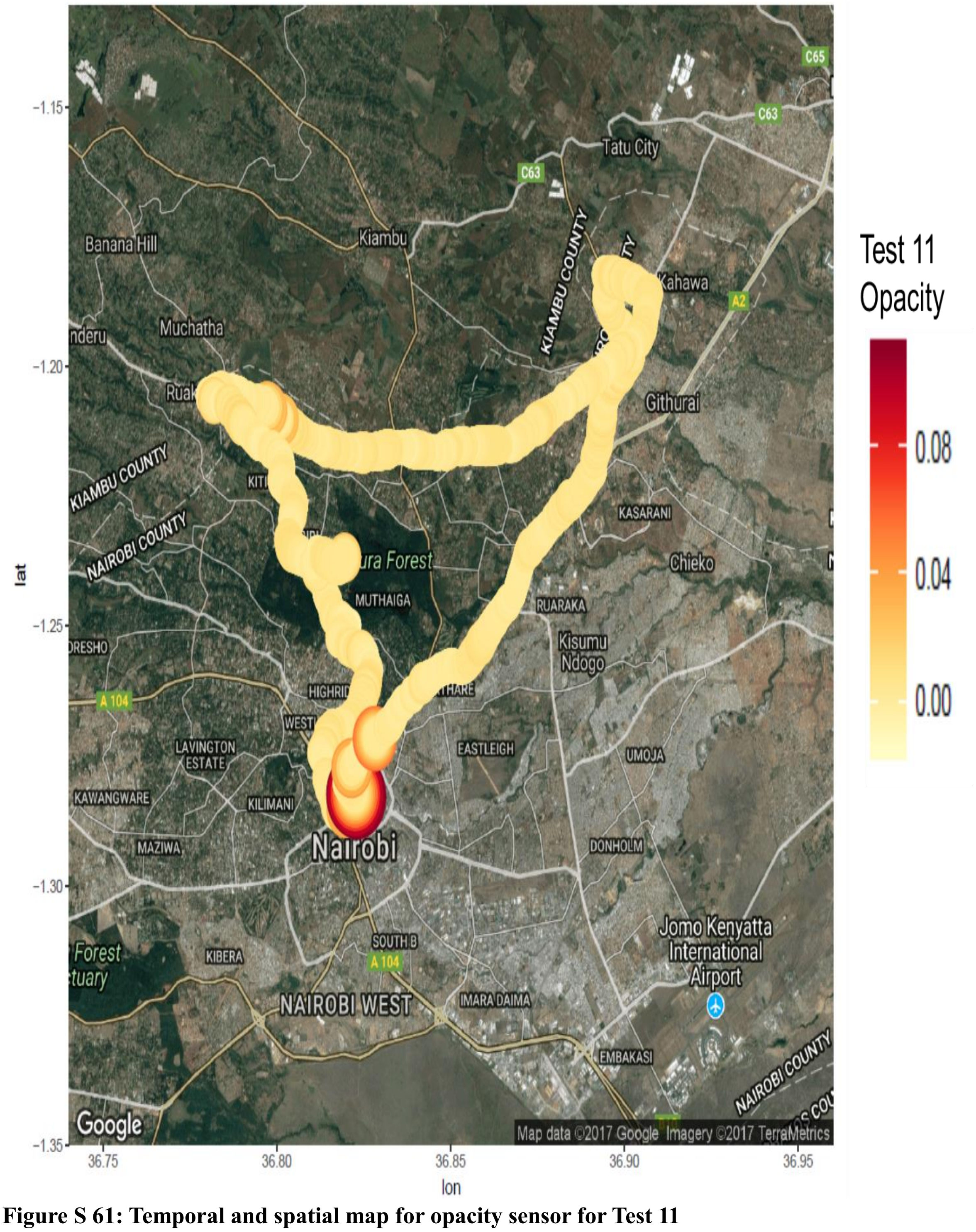


Figure S 61: Temporal and spatial map for opacity sensor for Test 11

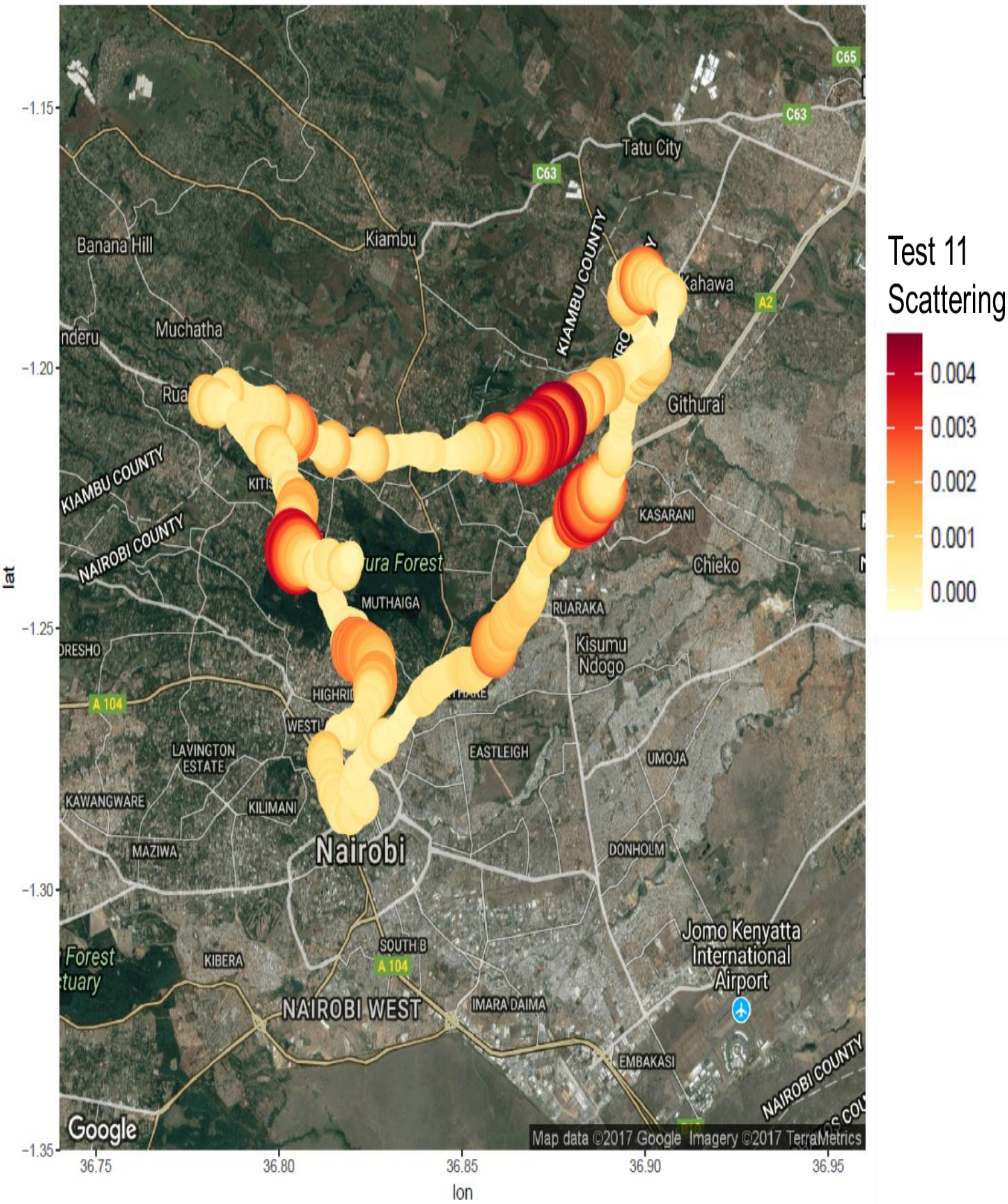


Figure S 62: Temporal and spatial map for scattering sensor for Test 11

Chapter 3

The work outlined in this chapter has been adapted from a research paper prepared for publication. I undertook all data analysis, but Dr Jan R. Böhnke helped to write the algorithm for the fuel economy modelling. Professor Mike R. Ashmore, Dr Jan R. Böhnke and my supervisors, Dr Lisa Emberson, Dr Harry Vallack and Dr Dietrich Schwela following an initial draft, made valuable contribution to the methodology, presentation of results, discussion through their inputs and manuscript editing. Their editing of the article upon which this chapter is based improved the clarity with which the fuel economy modelling framework and its rationale were presented.

3 Estimating vehicle fuel economy in Africa: A case study based on an urban transport survey in Nairobi

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Abstract

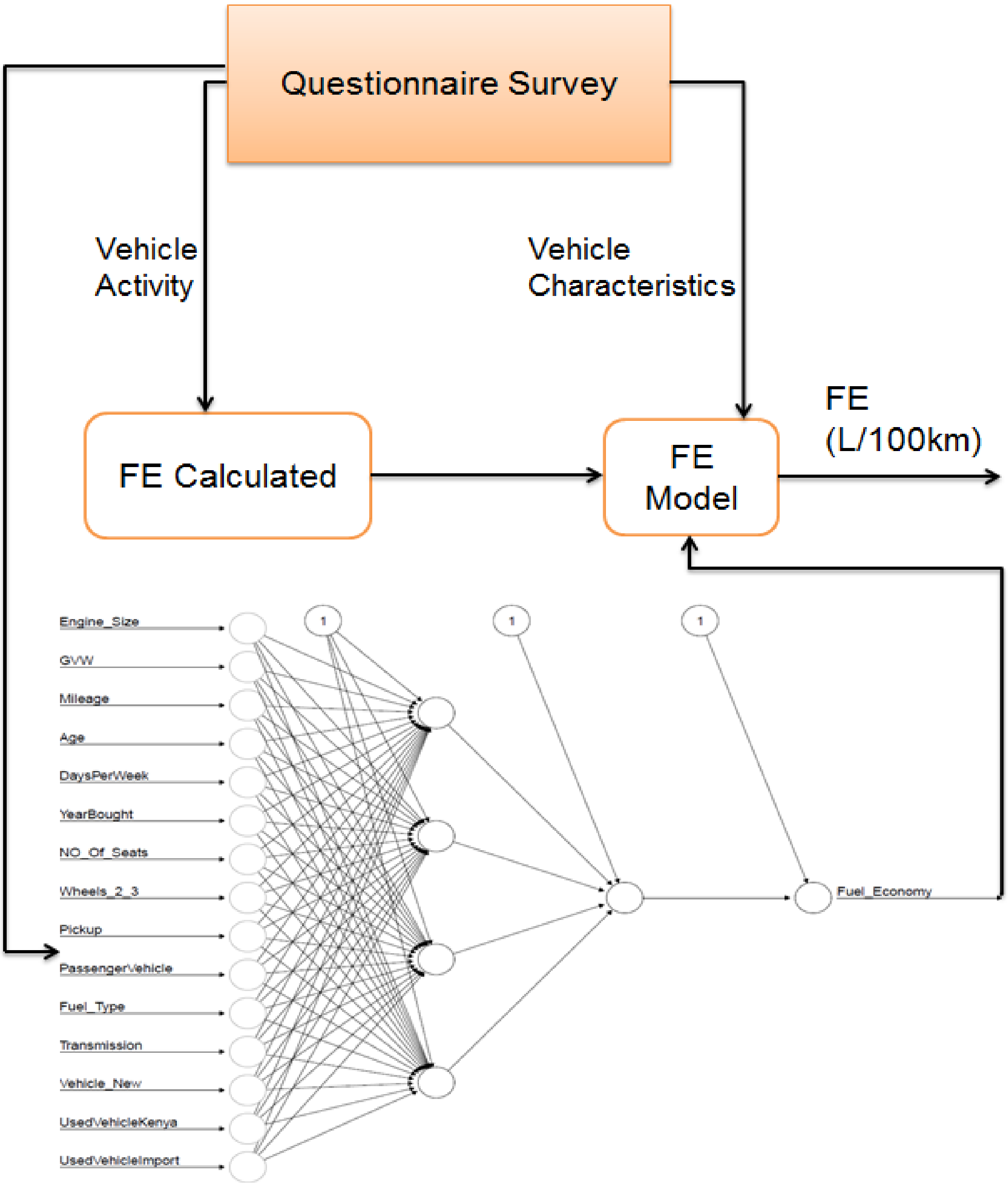
In sub-Saharan African (SSA) cities like Nairobi, the lack of vehicle-related data is a major challenge when developing environmental policies for the transport sector. In such cities, policies to improve vehicle fuel economy could help to reduce greenhouse gas emissions and improve air quality. We present a methodology for estimating fuel economy within developing countries using questionnaire surveys. Vehicle characteristics and activity data, for both the formal fleet (private cars, motorcycles, light and heavy trucks) and informal fleet (minibuses (*matatus)*, three-wheelers (*tuktuks*), goods vehicles (*AskforTransport*) and two-wheelers (*bodabodas*)), were collected and used to estimate fuel economy using both general linear modelling (GLM) and artificial neural network (ANN) approaches.

Fuel economy for *bodabodas* (4.6±0.4 L/100 km), *tuktuks* (8.7±4.6 L/100 km), passenger cars (22.8±3.0 L/100 km), and *matatus* (33.1±2.5 L/100 km) was found to be 2-3 times worse than in the countries these vehicles are imported from, partly reflecting their relatively high age. Of the two models investigated, the GLM approach provided the better estimate of predicted fuel economy. Here we provide a methodology and statistical analysis of survey data, for both informal and formal urban fleet, to help meet the challenge of a lack of availability of detailed vehicle data in SSA cities.

Keywords

Africa, *Matatu, Bodaboda*, GHGs, Air Pollution, in-use vehicle, informal transport

Graphical Abstract



Highlights

- Vehicle fleet characteristic and activity data collected with questionnaire survey.
- Key missing data not collected in the survey estimated using multiple imputations.
- General Linear Model predicted in-use fuel economy from survey data.
- Kenya-specific vehicle types, *Matatus* and *Bodabodas*, have poor fuel economy.
- Fuel economy is 2-3 times worse in Nairobi compared to developed countries.

3.1 Introduction

One approach to mitigating the impacts of air pollution on human health, and impacts of greenhouse gases (GHGs) on climate is to reduce the growth of vehicle fuel consumption by improving fuel economy (Ribeiro *et al.*, 2007; IEA, 2011, 2012a; Schipper, 2011; Bandivadekar *et al.*, 2016; Plotkin, 2016). Since fuel economy is a good indicator of GHG emissions it has become an important metric to assess trends and allow comparisons in GHG emissions between different vehicles as well as between vehicle fleets from different world regions. It is also a key indicator by which vehicle manufacturers assess compliance with GHG emission targets. As such, making reliable assessments of fuel economy for in-use vehicle fleets is an important policy tool for helping to target emission reduction policy (Plotkin, 2016).

To estimate in-use fuel economy of a vehicle fleet in a typical sub-Saharan African (SSA) city such as Nairobi, one needs data to describe the fleet composition, characteristics and activity for in-use vehicles. Moreover, these data need to include the total number of vehicles disaggregated by vehicle type, fuel type, age, emission technology and annual mileage (i.e. vehicle kilometres travelled (VKT) per year (Goel *et al.*, 2014, 2015; Kholod *et al.*, 2016).These data may be found in vehicle registries but these are often incomplete, inaccurate, inconsistent and outdated in developing countries (Agyemang-Bonsu *et al.*, 2010; Goel *et al.*, 2014; Kholod *et al.*, 2016). Often national vehicle registries do not portray actual vehicle distribution on city roads, for example, vehicles registered in Nairobi may be in circulation elsewhere (Kholod *et al.*, 2016). A particular challenge arises from the growing use of informal transport in SSA such as the use of *matatus* (Venter and Mohammed, 2013; Ommeh *et al.*, 2015; Behrens *et al.*, 2017), *bodabodas* (Kumar and Barrett, 2008; Kumar, 2011) and *tuktuks* (Cervero and Golub, 2007) . These vehicles tend to be unregistered (making it difficult to use standard fleet inventory methods to capture their contribution to urban traffic) as well as being old, poorly maintained and overloaded during use; all factors that will increase tail-pipe emissions resulting in enhanced air pollution (Cervero and Golub, 2007; Assamoi and Liousse, 2010). Thus developing methodologies that can capture this unique but important component of the vehicle fleet in SSA cities is crucial for the development of representative assessments of the contribution of the transport sector to the atmospheric pollution burden. To address these data shortages, traffic video and parking lot surveys are often conducted and these data used as input for traffic models (Lents *et al.*, 2005; Goel *et al.*, 2014, 2015; Kholod *et al.*, 2016). These types of survey however, face various challenges, for example, in determining VKT, type of vehicle, age and emission technologies on the vehicle (UC Riverside, 2002; Lents *et al.*, 2004, 2005). To overcome some of these challenges, previous studies in Nairobi, have made certain assumptions which no longer hold, such as, the licence plate data standing as a proxy for the age and mileage of the vehicle (Lents *et al.*, 2004).

Globally, governments have developed and implemented fuel economy policy and standards that specifically target fuel consumption to reduce GHGs. Such policies and standards, have been implemented in four of the largest vehicle markets: USA, China, EU, and Japan (Plotkin, 2004, 2016; Ribeiro *et al.*, 2007; Tietge *et al.*, 2017). Policies and standards in other major global markets (Australia, Brazil, India, Mexico and South Korea) tend to harmonize with these larger markets (Plotkin, 2016). Vehicle fuel economy and consumption are terms that are often used interchangeably in the literature (Huo *et al.*, 2012; Slavin *et al.*, 2013; TÜV Nord, 2013; Ntziachristos *et al.*, 2014; Bandivadekar *et al.*, 2016; Hao *et al.*, 2016; Haq and Weiss, 2016; Plotkin, 2016; Tietge *et al.*, 2017). Within this study, fuel economy will refer to volume of fuel consumed per distance (L/100km) and fuel consumption will refer to volume of fuel consumed over time (L/day). Kenya does not have fuel economy standards (Cameron *et al.*, 2012). A previous study estimated Kenyan fuel economy to be near equivalent to European and Japanese standards lagged by 8 years(ERC, 2015b). In that study an assumption was made in the absence for in-use vehicle activity data for the Kenyan fuel economy fleet to be equivalent to European fleets of the same year of manufacture; in addition the study only covered newly registered vehicles light-duty vehicles and not vehicles in circulation.

Vehicle manufactures declare fuel economy for new vehicles determined by chassis dynamometer testing of representative vehicles under laboratory conditions (Posada and German, 2013; Tietge *et al.*, 2017). However, there is usually a discrepancy between laboratory tests and on-road values as laboratory conditions cannot reflect real-world driving conditions in a vehicle's lifetime (Weiss *et al.*, 2011; Posada and German, 2013; Pandey and Venkataraman, 2014; Zhang, Wu, Liu, Huang, *et al.*, 2014; Tiege *et al.*, 2015; Plotkin, 2016; Tietge *et al.*, 2017). Furthermore the underestimation of actual fuel economy in laboratory type-approval testing directly affects achievable GHGs reductions (Ntziachristos *et al.*, 2014). Measuring on-road fuel economy has been undertaken using portable measuring monitoring systems (PEMS), but this is expensive and time consuming as measurements are only provided for a single vehicle over a short time period (Posada and German, 2013). Therefore, real-world fuel efficiency emission data are often lacking especially in developing countries (Weiss *et al.*, 2011; Hu *et al.*, 2012).

Estimating fleet fuel economy of in-use vehicles is difficult as it varies with a number of other factors such as: the number of vehicles, fleet composition, vehicle characteristics, vehicle activities, fuel type and quality, congestion, driving style, road type, inspection and maintenance and degradation (Smit *et al.*, 2008; Zhang, Wu, Liu, Ruikun, *et al.*, 2014). Prior studies have noted the importance of determining in-use fleet fuel economy especially with vehicles with accumulated mileage over 500 000 km (Boulter *et al.*, 2009; Pillot *et al.*, 2014). USA and European environmental agencies factor in deterioration rates for vehicles under this mileage, but engines now last over 800 000 km before requiring the first rebuild of the engine (Pillot *et al.*, 2014). These very high mileages are typical in vehicle fleets in SSA, and the costliness of studies and limited resources are even more of a hindrance when determining in-use fuel economy. Where these data are available, they can be used to estimate current GHG emissions, establish baseline emissions and explore future emission scenarios for a changing vehicle fleet. As such, knowledge of current emissions is crucial to the development and implementation of emission reduction policy measures which are currently lacking in SSA (Schwela, 2012) . In addition, lack of vehicle activity data in formulating Intended Nationally Determined Contribution (INDC) for the transport sector (Cameron *et al.*, 2012), as set out by United Nations Framework Convention on Climate Change mitigation (United Nations, 1992), has been identified by national governments in SSA as a major challenge in determining priorities in transport mitigation options.

Mathematical models for predicting fuel economy have been developed using vehicle physical characteristics such as engine size, maximum vehicle power, vehicle torque, vehicle weight, wheelbase and cross-sectional area (Cappiello *et al.*, 2002; Slavin *et al.*, 2013; Oh *et al.*, 2014). The development of one such model required a large detailed historical dataset of new light duty vehicles, n = 6 246, with highway fuel economy data and corresponding vehicle characteristics (Slavin *et al.*, 2013). In that study, the fuel economy was assumed to be as declared by the manufacturers as per corporate average fuel economy (CAFÉ) standards. This level of quality and quantity of data is rarely available, especially for developing countries (Ibarra-espinosa *et al.*, 2017). Furthermore, the fuel economy declared for new vehicles is extremely unlikely to be transferable to the majority of the in-use, often old and second-hand, vehicle fleet in developing countries (Goyns, 2008).

The overall objective of this paper is to develop a vehicle fleet questionnaire survey and associated procedure whose applicability is demonstrated for Nairobi Metropolitan Region (NMR), Kenya, allowing for the collection of primary data that includes characteristics such as engine size, weight of vehicle, mileage, money spend on fuel, transmission, age of vehicle, fuel type and vehicle utility. These primary data (mileage and the money spend on fuel) are used to calculate fuel economy. We also use a statistical method, multiple imputation, to deal with missing data (Honaker et al., 2011), a common problem with surveys. To the authors' knowledge, this approach for dealing with missing data has not previously been applied in vehicle survey data. The secondary data, obtained from existing literature, are used to determine the total number and composition of vehicles as well as to verify primary data describing vehicle characteristics. These verified primary data, when used in conjunction with secondary data, give a baseline of real-world vehicle characteristics and activity for in-use vehicles. Further, this paper demonstrates how to use previously applied methodologies to build mathematical models to predict fuel economy; here we use and compare generalized linear models (GLM) and artificial neural networks (ANNs) (Slavin et al., 2013; Alice, 2015). These methods have the potential to be rapidly deployed in other SSA cities and regions which suffer from similar data limitations and resources and importantly are able to capture the variability in the vehicle activity and emission data that exists both in the formal and informal vehicle fleets.

3.2 Methodology

Nairobi and the larger Nairobi metropolitan region (NMR) was chosen as the site of the study as Nairobi is a typical SSA city in terms of socioeconomic status , size and population growth (UN-HABITAT, 2014). The total population of the NMR is 6.7 million people as of 2009 (KNBS, 2013a). Nairobi is the largest city in Kenya and the 14th largest in Africa with a population of 3.9 million people.

Figure 3.1 describes the data combinations required to develop the NMR vehicle fleet dataset and how this is then used to estimate fuel economy using the three different modelling approaches: calculated fuel economy, GLM and ANN. The modelling approaches used to estimate in-use fuel economy (FE) for the on-road vehicle fleet in Nairobi require data describing vehicle characteristics and vehicle activity as listed in Figure 3.1. Primary data were collected using a questionnaire survey (see supplementary information, S1). Secondary data were used to determine the total number of vehicles and fleet composition as well as to verify the fleet compositions and characteristics derived from the questionnaire survey primary data collection (i.e. vehicle characteristics: vehicle weight, engine size).

3.2.1 Secondary databases

The total number of vehicles and fleet composition for vehicles in Kenya were obtained from the Kenya National Bureau of Statistics (KNBS) (KNBS, 2014b) . The composition of the vehicles in NMR were obtained from a transport feasibility surveys (JICA, 2006, 2014). Vehicle registration data for all light duty vehicles in Kenya from 2010-2012 were obtained from a global fuel economy initiative (GFEI) between the Partnership for Clean Fuels and Vehicles (PCFV) of United Nations Environment Program (UNEP) and the Energy Regulatory Commission of Kenya (ERC) (ERC, 2015b). Data describing the total number of vehicles was used to determine the sample size required for the questionnaire survey. The NMR fleet composition was used to determine the sample weighting of the different vehicle categories for the field survey.

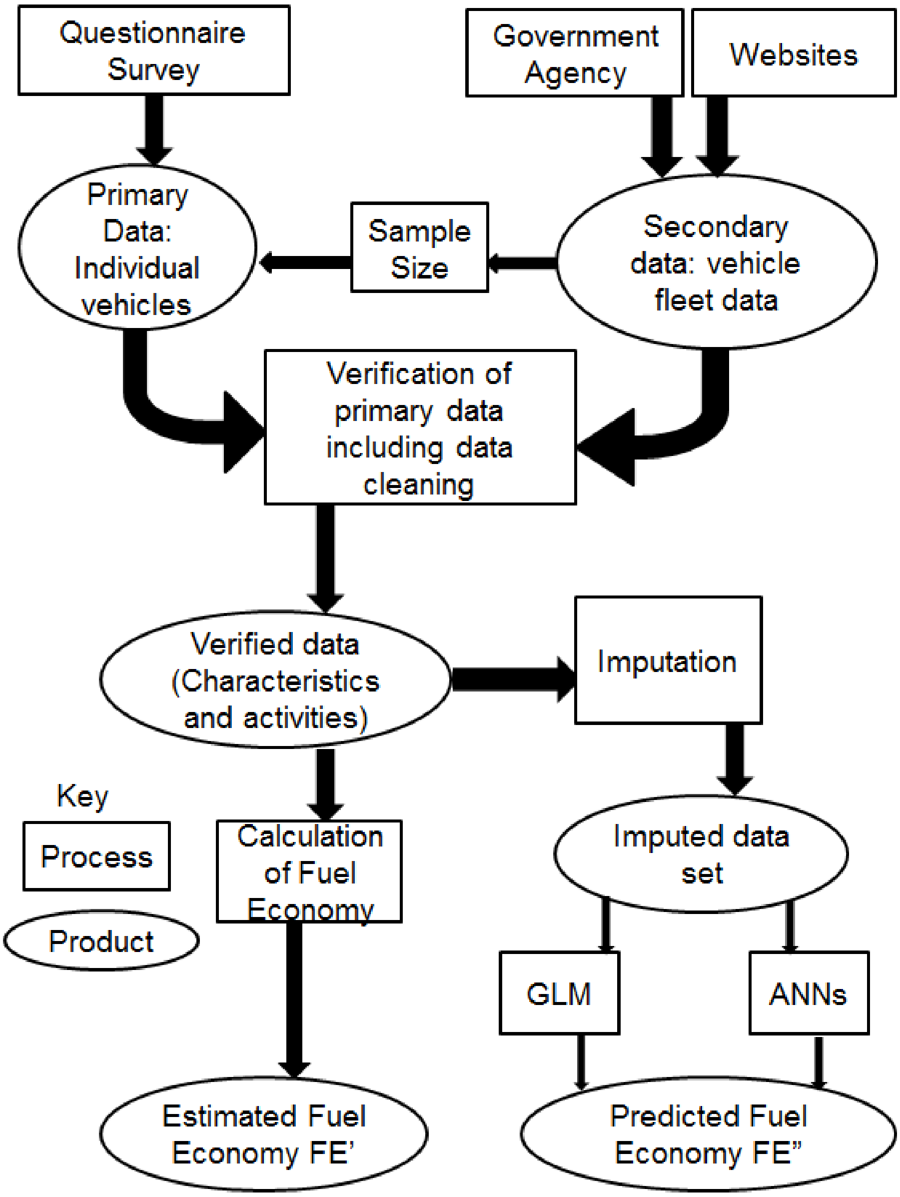


Figure 3-1: The data combinations required to develop the NMR vehicle fleet dataset and estimate fuel economy using the three different modelling approaches: calculated fuel economy, GLM and ANN.

3.2.2 Questionnaire survey

A questionnaire-based quantitative vehicle fleet survey was developed to collect data for the 18 variables describing vehicle characteristics and vehicle activity and trialled in Nairobi (see Table 3.1). These variables provided information on fleet composition, fuel consumption, technology, age of the vehicle, VKT, occupancy, and passenger load from data gathered from pedestrians and drivers.

Table 3-1: 18 variables identified from questionnaire survey data divided into two categories: numerical data and categorical data.

Numerical Data	**Categorical data**
Unique vehicle identifier code	Type of vehicle
Engine size (cc)	Fuel type
Gross vehicle weight (kg)	Manufacturer
Odometer reading	Model
Year of vehicle manufacture	Transmission
Day per week the vehicle travels (days/week)	Vehicle ownership (owns or drives vehicle)
Average distance vehicle travels a day (km/day)	Condition (new/used)in which vehicle was bought
Year(s) ago vehicle was bought (Years)	
Average money spend on fuel per vehicle (Ksh/month)	
Number of seats in a vehicle	
Litres of fuel used per vehicle (L/month)	

The face-to-face questionnaire survey interviews were conducted from December, 2014 to January, 2015. Interviews were conducted by two trained interviewers between 10:00 -17:00 hrs at 15 sites across NMR. These sites were selected for their high vehicle density and pedestrian populations and included sites in parking lots, shopping centres, markets, *matatu stops*, *matatu* and bus terminals, city centre, and residential areas. The location of the NMR field sites are shown in Figure 3.2. To ensure the survey responses were as representative as possible, sites were also selected to include high, medium and low income groups; with a stratified sample of vehicle users from different socio-economic classes being interviewed as they arrived randomly.

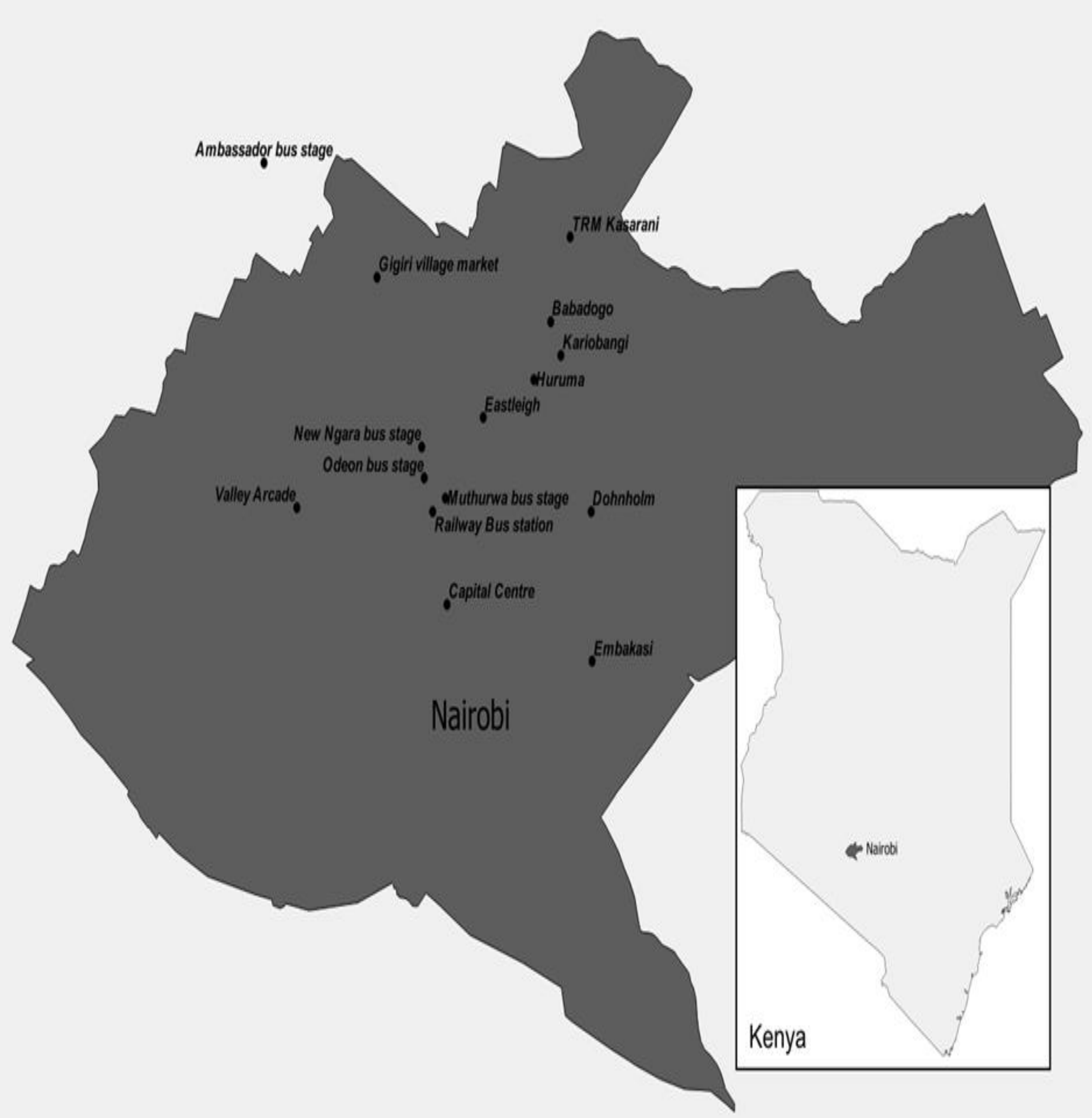


Figure 3-2: A Map of the 15 field sites where the questionnaire survey interviews were conducted in NMR. The map was created using GRASS software (GRASS Development Team, 2015).

The secondary data describing the population of registered cars in Kenya (KNBS, 2014b) was used to estimate that 67% of vehicles are located in the NMR (Gachanja, 2012), this amounts to 1.35 million vehicles. Following the procedure (Van Dessel, 2013) a target sample size of n=1 284 for the questionnaire survey was required to obtain a 95% confidence interval with a ±5% margin of error assuming a conservative estimate of mail survey response rate of 30% (Fincham, 2008). Out of the 836 persons invited to participate in the survey, 824 responded (98.6% response rate), this surpassed the response rate and the sample size was deemed to be sufficient.

Table 3.1 summarises the 18 data variables the survey was designed to collect, divided into continuous data (with numerical specifications) and categorical data (with qualitative attributes). The questionnaire response was split by vehicle types as follows: passenger cars comprising private cars, company cars and taxis (243), *matatus* (250), *bodabodas (233)*, motorcycles for personal use (11), *tuktuks* (16), light goods vehicles (58), and heavy goods vehicles (13). The descriptions of these vehicle types are found in Table 3.2.

3.2.3 Verification of vehicle characteristics

Secondary data from various second-hand sales websites (Japan Car Direct, 2015; Be Foward Co, 2017; Cheki Inc., 2017; PigiaMe, 2017) and information from vehicle manufacturers (Isuzu Kenya, 2014; Toyota Kenya, 2014, 2017; Nissan Kenya, 2017; Toyota, 2017) were used to verify and adjust: weight, engine size and year of manufacture for the vehicles in the survey sample. The questionnaire responses relating to the manufacturer and model type were adjusted according to the information available on the manufacturers' and second-hand sales websites, in order to reduce inconsistencies in the data. For instance, certain vehicle makes and models are manufactured for a specific year or period and these websites have the vehicle specifications for the vehicles on sale such as weight, engine size, transmission, these data were used to ensure survey responses were correct for those categories that could be verified.

3.2.4 Statistical descriptive analysis by vehicle class

To help describe, summarize and compare the different vehicle types the questionnaire survey data were divided into subsets split by Kenyan vehicle class. This was achieved by allocating the Kenyan vehicle classes to EU vehicle classes according to the EMEP/EEA classification (Kouridis *et al.*, 2014). These EU classes were used since EU classifications are frequently employed to categorise default emission factors in emission inventories. The use/utility of the vehicles in Kenya are typically different from the EU, for example, 8 passenger vans are converted to 14 seater *matatus* and motorcycles (*bodaboda*) are used for public transportation. In these instances we kept certain unique Kenyan vehicle classes that represent the informal vehicle fleet (e.g. *matatus*, *bodabodas*, *tuktuks, Askfortransport*) but related these to an equivalent EU emission class.

Descriptive analyses were conducted to determine statistical parameters of the primary data from the questionnaire field survey using R (R core team, 2016). The statistical parameters: mean, median and standard error with 95% confidence interval were calculated for all numerical data.

3.2.5 Estimated fuel economy determined using fuel consumption and mileage

Three variables from the descriptive analysis: average days per week a vehicle travels (days/week), average distance vehicle travels per day (km/day) and average money spent on fuel per vehicle (Ksh/month), were used to determine fuel consumption (FC) and mileage (VKT), which was in turn was used to calculate fuel economy, denoted as FE'. FC (L/day) was calculated using the amount of money spent on fuel/month per vehicle using a baseline price for 15/November/2015 at the average fuel pump price of Ksh. 84.23 per litre of diesel and Ksh. 93.29 per litre of petrol assuming 30 calendar days per month (ERC, 2015a). FE' is calculated from the fuel consumption per day (L/day) and the average distance travelled using equation 3.1 and equation 3.2.

Fuel consumption per day (L/day):

$$FC\ \left(\frac{L}{day}\right) = \frac{\dfrac{Total\ money\ spend\ on\ fuel\ per\ month(\frac{Ksh}{month})}{Cost\ of\ fuel\ (\frac{Ksh}{L})}}{No\ of\ days\ per\ month\ (\frac{day}{month})} \qquad Equation\ 3.1$$

Fuel economy (L/100 km):

$$FE' \ \left(\frac{L}{100km}\right) = \frac{FC \ \left(\frac{L}{day}\right)}{VKT\left(\frac{km}{day}\right)} * 100 \qquad\qquad Equation\ \ 3.2$$

3.2.6 Identify and screen for implausible questionnaire survey data

Implausible vehicle activity data were identified, screened and excluded based on data in the literature. FE for the most and least advanced internal combustion vehicle technology and fuels available in the world was used as a boundary limit (Bandivadekar *et al.*, 2016). This was based on the assumption that the best internal combustion technologies can only perform to a certain maximum efficiency giving an upper and lower limit for fuel economy for each vehicle. The lowest and highest fuel economy baseline and cut off was set for passenger vehicles at 5 L/100km and 100 L/100km (Bandivadekar *et al.*, 2016); and for 2-wheelers for the best and poorest fuel economy to be greater than 1 L/100km and less than 10 L/100km (Total Motorcycle, 2017). Using these criteria, 19 vehicles whose estimated fuel economy fell outside these acceptable ranges were identified and excluded from the passenger car and 2-wheeler categories. Detailed data of the excluded vehicles is shown in the supplementary section, Table S1.

3.2.7 Fuel Economy (FE'') modelled using a general linear model (GLM) and Artificial Neural Network (ANN)

Here we build on and extend a methodology used for light duty vehicles in the USA (Slavin *et al.*, 2013). The authors predicted FE using a detailed historical data set of n = 6 246 vehicles. Their dataset contained fuel economy data allowing evaluation of a model that estimated FE" from corresponding vehicle characteristics: engine size, engine power, torque, vehicle weight, wheel base and cross sectional area. A least squares regression model and an ANN model was then applied to create a more accurate predictive FE'' model. In the absence of fuel economy data per vehicle category in secondary data in Kenya, equation 3.1 and 3.2 were used together with primary data from the questionnaire to calculate FE', ANN and GLM was then applied to create a model that is capable of more accurate prediction of FE according to vehicle characteristics.

Our vehicle fleet questionnaire data collected in NMR was dissimilar in that it was a smaller data set n= 824 and it missed some of the vehicle physical parameters unlike a dataset from vehicle manufacturer such as the case with the CAFÉ standards (NHTSA, 2014).These data collected in NMR (shown in Table 3.1) included vehicle characteristics and activity data for in-use fleet: light duty vehicles, heavy duty vehicles, motorcycles and mopeds. Given the differences in data, the Slavin et al., (2013) methodology was altered to first calculate fuel economy using equation 1 and 2 and then a general linear model (GLM) used to create a predictive fuel economy model (Alice, 2015). The accuracy of the GLM model was compared to ANN model.

The equation relating fuel economy in Slavin et al., (2013) to vehicle physical parameters was adjusted to incorporate 11 variables to explore variable importance in determining key drivers influencing FE''; the general relation is shown in equation 3.

$$FE'' = f(VTU, FT, TT, CC, GVW, MIL, Age, DPW, YBT, NU, NOS) \qquad Equation\ 3.3$$

- Modelled Fuel Economy (FE”)
- Vehicle type and utility (VTU)
- Fuel type (FT)
- Transmission Type (TT)
- Engine size (CC)
- Gross value weight (GVW)
- Mileage on the car from cumulated odometer reading (MIL)
- Age of vehicle as a proxy for technology (Age)
- Days per week vehicle used (DPW)
- Vehicle turnover from years since vehicle bought by current owner (YBT)
- Condition in which the vehicle was originally purchased (NU)
- Number of seats on vehicle (NOS)

Vehicle type and utility (VTU) were re-coded into three dummy variables representing 3 broad classes: passenger cars, 2-wheelers and 3-wheelers and light commercial vehicles. Heavy duty vehicles were used as a reference category. Fuel type (FT), transmission (TT), and condition of the vehicle when it was originally purchased (NU) were similarly recoded. In recoding the NU variable, vehicles bought new (NN) were used as a reference category. The dependent variables were then transformed using natural logarithm.

While a GLM fits only linear and direct associations between the set of predictor variables and the dependent variables, ANNs are more flexible and deal with non-linearity more accurately (Nagendra and Khare, 2005) . An ANN proposes an input as well as an output layer of information, the input being our set of predictor variables and the output being FE" as outlined in Equation 3.3. The network then further assumes that a number of layers exist that transform the input optimally to predict the output. Such transformations could be equivalent of a GLM (no layers between input and output, only direct associations between the two layers), but usually at least one layer is assumed that consists of so called "nodes" where the input from several variables is combined to produce a new output (see arrows in graphical abstract). The input from such a layer of nodes could again be combined by a new layer of nodes etc. This way, neural networks are very flexible in modelling linear and non-linear interaction terms between input variables. The whole network is optimised to maximise predictive power for the output layer (which can in principle consist of more than one variable). The final model depends on trying a range of different network configurations and comparing their predictive power, therefore the whole process depends on guarding against over-fitting, which will be described in the following section.

When fitting the GLM and ANN models (see Slavin et al., 2013 and Alice et al., 2015 for further details) the analyses needed to account for two specific problems. First, missing data needed to be dealt with in a manner that is statistically appropriate and that takes sampling variance into account. Second, we need to guard against over fitting our FE" model based on just a single sample. The following steps (a) to (f) were taken to address these problems:

a) Multiple imputation of missing data

Multiple imputation of incomplete multivariate data, a well-established methodology for dealing with missing data (Horton and Lipsitz, 2001; Kenward and Carpenter, 2007; Azur *et al.*, 2011) was applied to the dataset using R statistical package AMELIA (Honaker *et al.*, 2011). Imputation has previously been applied to medical and psychiatric research (Burton *et al.*, 2007; Kenward and Carpenter, 2007; Azur *et al.*, 2011; Biering *et al.*, 2015). Before the main analysis, 20 imputations were run to examine the accuracy of imputation and to check how close the imputed density distributions and bivariate distributions were to the original values.

b) Split imputed dataset into estimation and valuation data

After imputation, the dataset was randomly split into a training dataset constituting 75% of the imputed dataset and 25% of the remainder was used as a test dataset.

c) Fit general linear regression model and compute mean square error (MSE)

A general linear model (GLM) regression was fit to the training split of the imputed dataset and mean square error (MSE) was computed on the test split of the data.

d) Neural network model-exploratory phase

A neural network model was applied to the imputed dataset using Levenberg-Marquardt back-propagation algorithm. This was created using a neuralnet package (Fritsch *et al.*, 2016) and closely followed existing methodology (Alice, 2015). The architecture had one or two hidden layers with various configurations which were determined experimentally. MSE, Bayesian information criterion (BIC) and Akaike information criterion (AIC) values for each of these models were calculated to evaluate model fit (MSE: how close the predictive fuel economy values were to the calculated fuel economy values; AIC/ BIC: how parsimonious the model fit was compared to the number of parameters needed to estimate the model). A selection of the top competing neural network (ANN) models based on the lowest MSE, AIC, and BIC numbers was identified to be included in the cross validation step alongside the GLM.

e) Cross validation

Cross validation was used in this step to measure the predictive performance of the models, to guard against over-fitting of the ANN, and to allow for model selection (Arlot and Celisse, 2010). Three competing ANNs had been selected from step d) based on the lowest AIC and BIC values as well as MSEs of comparable size to the GLM. An iterative bootstrap process was then used to estimate the predictive performance of all four models (Arlot and Celisse, 2010). At first a single imputation of the dataset was done and then the sample was randomly partitioned into a training set, 75% and a test set used as a validation sample, 25%. A GLM was then fitted to the training set and the MSE from predictions in the test set was saved. In the next step the three selected ANN structures were fit to this training data set, saving AIC and BIC values as well as their respective MSEs from their predictions in the test dataset. The cross validation process was iterated 1000 times with missing data imputation and randomised partitioning of the train-test dataset in each of the runs. For each iteration a comparative statistical analysis on MSE, AIC and BIC numbers was carried out to confirm best model estimate, thereby producing bootstrap distributions of the model fit criteria.

3.3 Results

3.3.1 Vehicle class, type and attributes

Using the EMEP/EEA classification (Kouridis *et al.*, 2014), 16 segment Kenyan vehicle classes were developed using the sample data based on vehicle weight, engine size and utility shown in Table 3.2. The distribution of the questionnaire data to these broad vehicle categories is also shown in Table 3.2. The category that had the largest number of questionnaire returns was *matatu*, followed by *bodaboda* and then private cars comprising of 250, 233 and 194 vehicle specific questionnaire response, respectively.

In developing the segments from the NMR fleet, special attention was paid to classify the informal portion of the fleet. *Tuktuk* and *bodaboda* had equivalent EMEP/EEA, L2e and L3e respectively. But the utility of the L3e in Kenya were different, both for private and public transport use. Thus L3e were further re-classified, motorcycles were those used for private transport and *bodaboda* were those used for public transport. *Matatu* were challenging to classify especially the 14 seater as these were imported as 9 passenger vehicles but refitted to seat 14 passengers. Hence, in EMEP/EEA classification, a 14 seater *matatu* would be a light duty vehicle (based on GVW less than 3500 kg), but we re-classified the 14 seater *matatu* to a heavy duty vehicles based on the number of passengers (greater than 8). The rest of the *matatus (26, 29, 33, 51, 62, 67 seaters)* were also classified as heavy duty passenger vehicles with sub-classes based on the number of passenger seats. The *AskforTransport* were classified as EMEP/EEA N1, N2 or N3 as they were either light duty commercial vans or trucks or heavy duty trucks. Light duty passenger vehicles included private cars, taxis, and company cars and were classified as EMEP/EEA M1, based on number of passengers (less than 8).

Table 3-2: Vehicle classification and categories for Kenyan vehicle fleet based on vehicle weight, engine size and utility of the vehicle. *Bodaboda*: two-wheeler used to ferry passengers and goods, *matatu*: minibus/bus taxi used to ferry passengers, *tuktuk*: three-wheeler used to ferry passengers and goods, *AskforTransport*: informal vans and truck for hire. Vehicle categories that often include informal transport types are identified in bold type.

EMEP/EEA Classification			Kenyan Class	Sample (Total)	Description	General
Light Duty Vehicle	Passenger vehicle: <8 seats	M1	AfritypeM1	243	Passenger cars <8	Includes private cars, company cars and taxis formal/informal
			AfritypeM1A	0	small car engine size<800cc	
			AfritypeM1B	21	medium car engine size 800-1400cc	
			AfritypeM1C	152	medium car engine size 1400-2000cc	
			AfritypeM1D	63	large car engine size >2000cc	
	Light goods vehicles	N1	AfritypeN1	51	GVW≤3500kg	Pickups, small trucks, ***AskforTransport***
Heavy Duty Vehicle	Passenger vehicles >8 seats	M2	AfritypeM2	84	1250kg<GVW <3500kg	**Matatu** 14 seater
		M3	AfritypeM3A	22	3500kg<GVW <6000kg	***Matatu*** >14 seater-26 seater
			AfritypeM3B	137	6000kg<GVW <8000kg	**Matatu** 29 seater-33 seater
			AfritypeM3C	7	8000kg<GVW <12000kg	**Matatu** >33 seater-51 seater
			AfritypeM3D	0	GVW>12000kg	**Matatu** 62-67 seater
	Heavy Goods vehicle	N2	AfritypeN2	9	3500kg≤GVW≤ 12000kg	Trucks, ***AskforTransport***
		N3	AfritypeN3	1	GVW>12000kg	Trucks, ***AskforTransport***
Motorcyle and Moped	Two-wheel	L1e	AfritypeL1e	0	Engine size <50cc	Motorbikes and ***bodaboda***
	Three-wheel	L2e	AfritypeL2e	16	GVW>270kg	***Tuktuk***
	Two-wheel	L3e	AfritypeL3e	244	Engine size >50cc	Motorbikes and ***bodaboda***

3.3.2 Vehicle characteristics

A portion of the descriptive statistics for the vehicle characteristics (before imputation) is shown in Figure 3.3. The vehicle characteristics presented are gross vehicle weight

(GVW) (kg), engine size (cc) and vehicle age (years) which is determined from the year the vehicle was manufactured. These data are shown for 11 of the 16 segments defined in Table 3.3 since there was insufficient data from the questionnaire data for the remaining 4 segments; engine size and weight were also missing for some of the vehicle categories.

The oldest vehicle age is for the type AfritypeM2 (14 seater *matatus*) at 16.9±0.2 years, and the lowest age is AfritypeLe (3 wheeler *tuktuks*) at 2.2±0.8 years, although AfritypeL3e (2 wheeler *bodabodas* and private motorbikes) are also relatively new with an average age of 2.7±0.4 years. Highest variability in the different vehicle classes in age was AfritypeM3C (33-51 seater *matatus*).

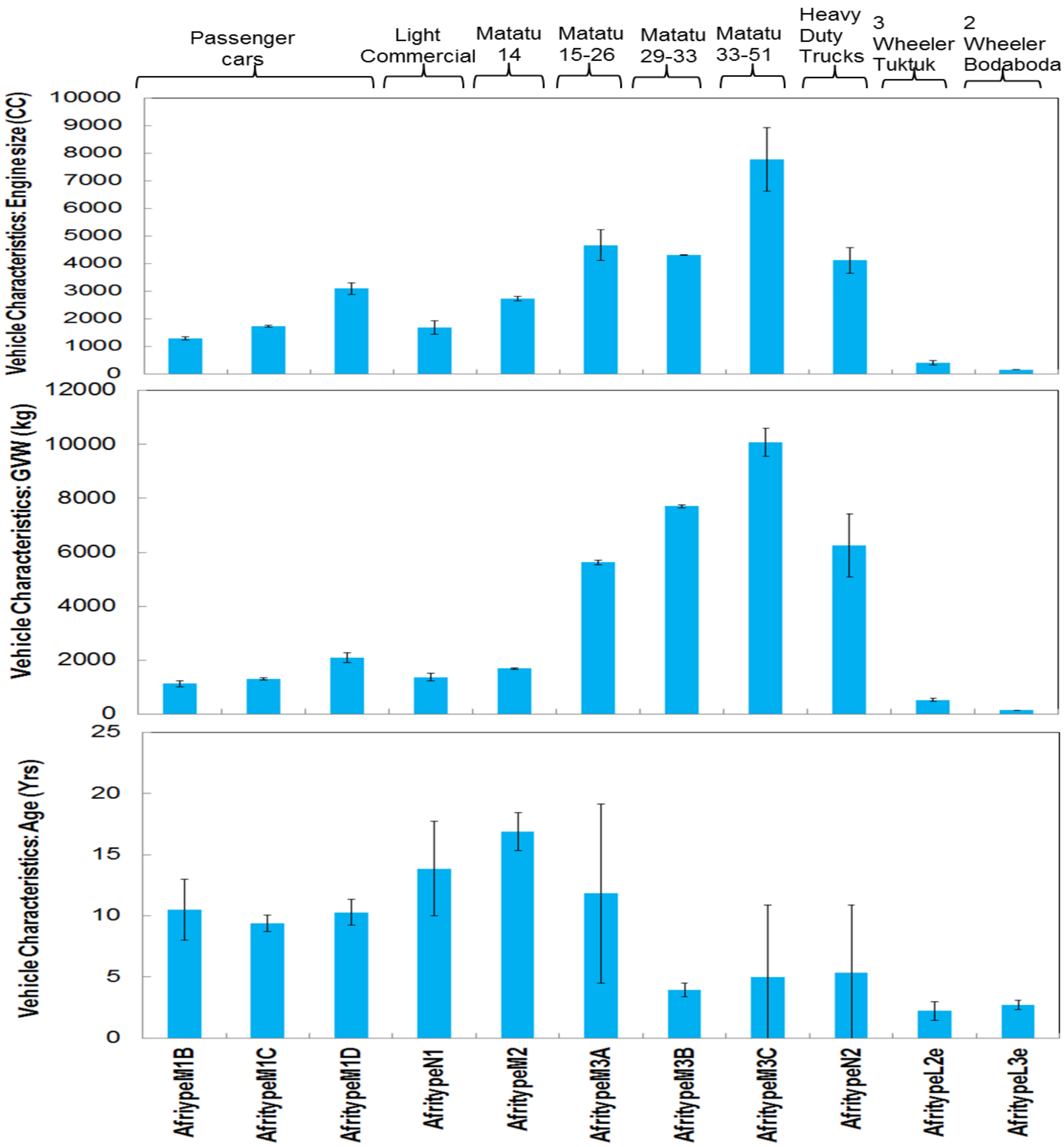


Figure 3-3: Vehicle characteristics from questionnaire data, mean with 95% confidence interval for vehicle age, engine size, and weight.

Engine size and vehicle weight are key vehicle characteristics in determining vehicle class together with the utility of the vehicle. Vehicle weight and engine size are predetermined from manufacture and grouped according to the Kenyan classes shown in Table 3.2. The heaviest vehicle weight and biggest engine size is for the type AfritypeM2C (33-51 seater *matatus*) and the least weight and engine size were the AfritypeL23e, the *bodabodas and* private motorbikes. Highest variability for weight was AfritypeN2 (heavy duty trucks) and for engine size was AfritypeM3C (33-51 seater *matatus*).

3.3.3 Vehicle activity

A portion of descriptive statistics for vehicle activity is shown in Figure 3.4. The vehicle activities shown are daily mileage calculated as vehicle kilometres travelled (VKT) per day (km), fuel consumption per vehicle (L/day), and the fuel economy (L/100km), for 11 of the 16 segments. The highest mean VKT (215.7 ± 60.5 km/day) and highest fuel consumption (63.2 ± 9.9 L/day) were both recorded for AfritypeM3C (33-51 seater *matatu)*. The highest mean FE' was found for AfritypeM3A (37.4 ± 5.4 L/100km), 14-26 seater *matatu*. The highest variability among the vehicle classes for fuel consumption and fuel economy was AfritypeN2 (heavy duty trucks) while highest variability for VKT was AfritypeM3C (33-51 seater *matatu*).

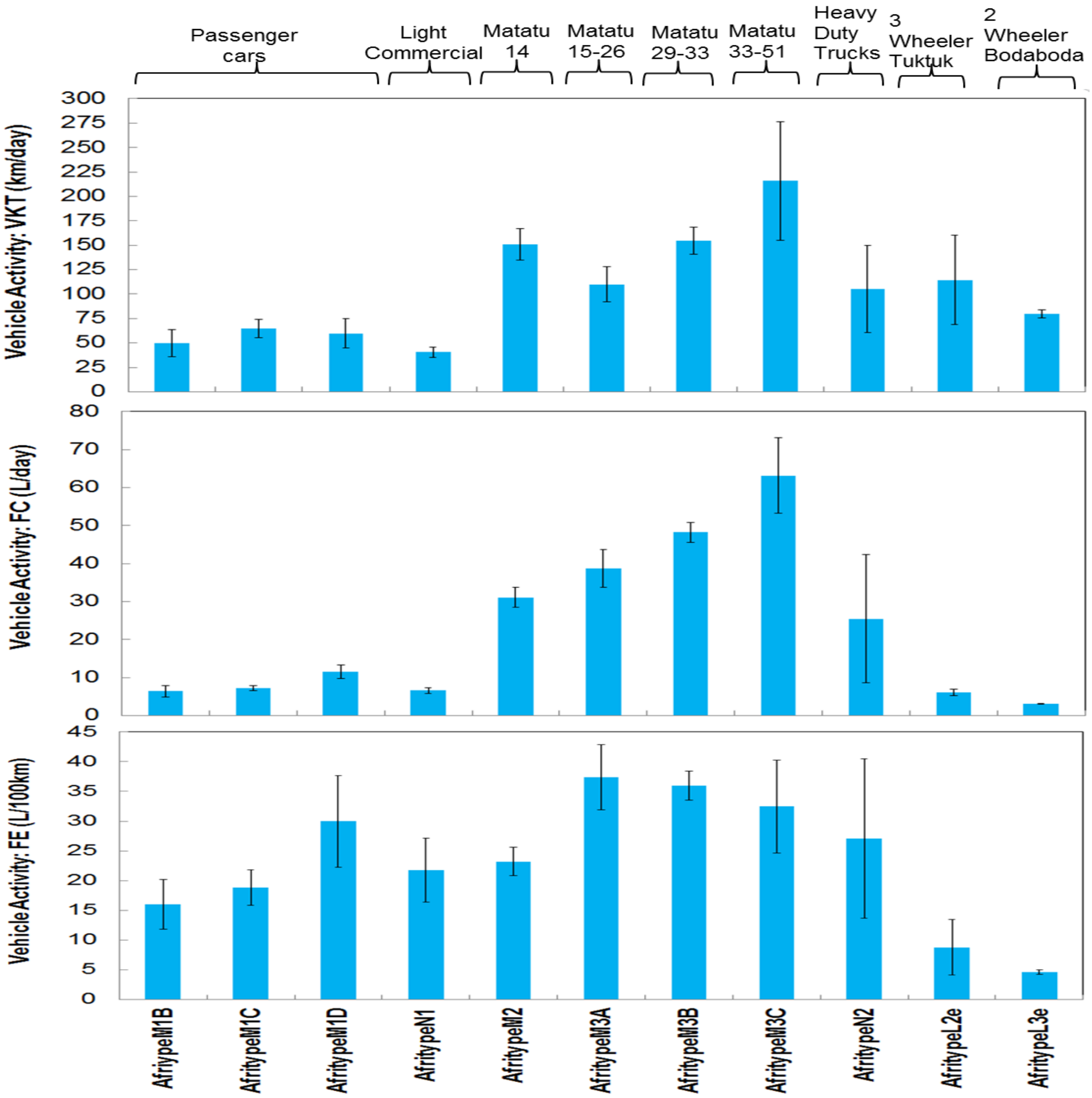


Figure 3-4: Vehicle activity from questionnaire data, mean and 95% confidence interval about the mean of the vehicle kilometres travelled (VKT), fuel consumption (FC) and Fuel Economy (FE') for Kenyan classes.

The differences in FE' between the vehicle classes as presented in Figure 4, were tested for statistical significance using Analysis of Variance (ANOVA). The variables compared in the test were the Afritype classification and the default classes from the questionnaires. FE' was found to be statistically highly significant $P < 2.2e^{-16}$ for N = 707, the table of results of the P-values resulting from this comparison is presented in supplementary section, Table S2.

3.3.4 Fuel economy model

3.3.4.1 Imputation

The data set before imputation is presented in Figure 3.5 which shows the map of missing values. The first 8 variables shown in columns in Figure 4 correspond with variables from equation 3 as follows: Age, MIL, YBT, GVW, DPW, CC, TT, FT. The first three: Age, MIL and YBT have the most missing variables. Before imputation only 36% of the dataset had a value for every variable, this improved to 89% after imputation with fuel economy not being imputed (which accounted for the remaining 11%).

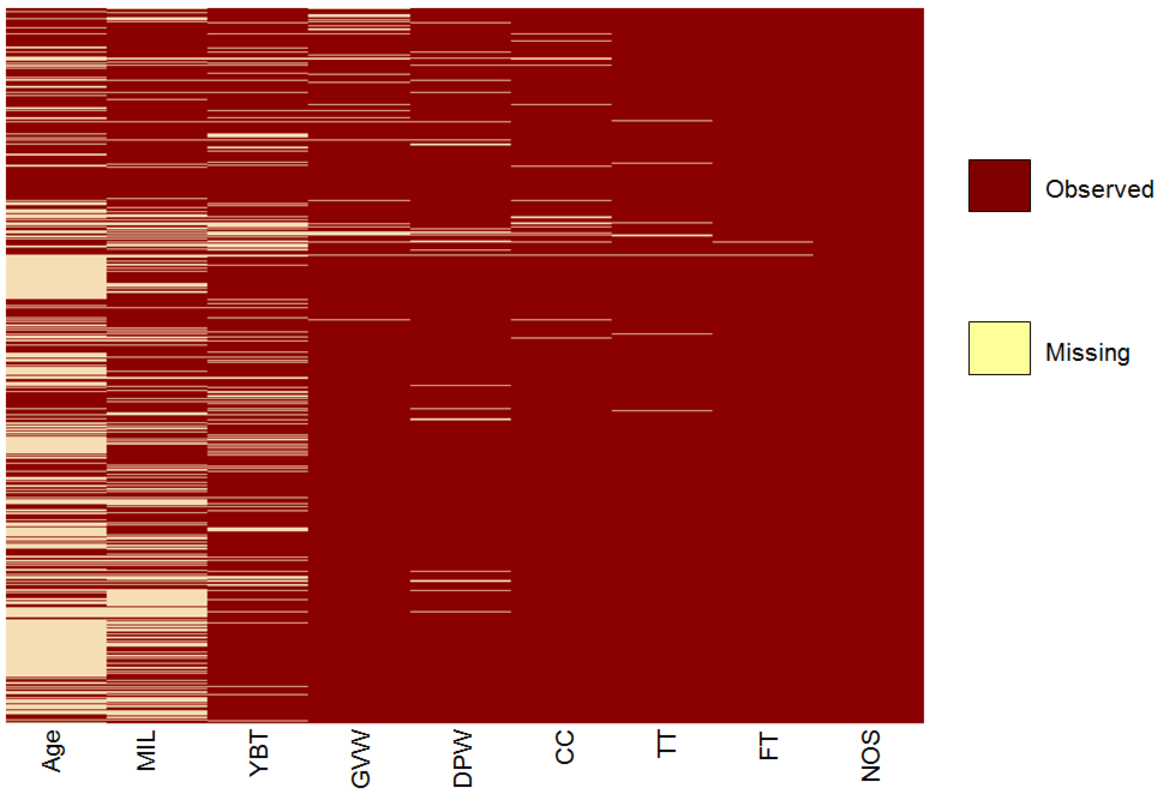


Figure 3-5: A map of missing values. The variables in columns correspond with those from equation 3 as follows: Age (Age of vehicle as proxy for technology), MIL (mileage on the car from cumulated odometer reading), YBT (vehicle turnover from years since vehicle bought by current owner), GVW (gross value weight), DPW (days per week vehicle used), CC (Engine size), TT (transmission type), FT (fuel type), NOS (number of seats on vehicle). The Y-axis presents the count of the different variables.

A plot of the diagnostics for the imputation is presented in Figure 3.6; the performance of the prediction algorithm is compared with that based only on the observed data. The dots in Figure 3.6 each represent an observed data point in our dataset, but they provide the mean imputed value that we would use in our analysis if this value had been a missing value. The x-axis orders these points according to their observed value while the y-axis presents this mean imputed value. The 90% confidence intervals around the means are based on 20 'overimputations' (Honaker *et al.*, 2011). The line in each plot presents the line of agreement, i.e. with perfect information all points would lie on this line (equivalence of observation and imputation) and we would expect 90% of dots to show an overlapping confidence interval with that line in each panel of the figure. The colours code the fraction of the missing values on the other covariates for that specific observed value. The results in Figure 3.6 show overall that the imputation worked reasonably for most variables with Engine Size (CC) and weight (GVW) being better imputed than Days per Week (DPW), which tend to be overestimated for the relatively few respondents who use their cars on four days or less. It is also worth noting that DPW had more missing values than CC.

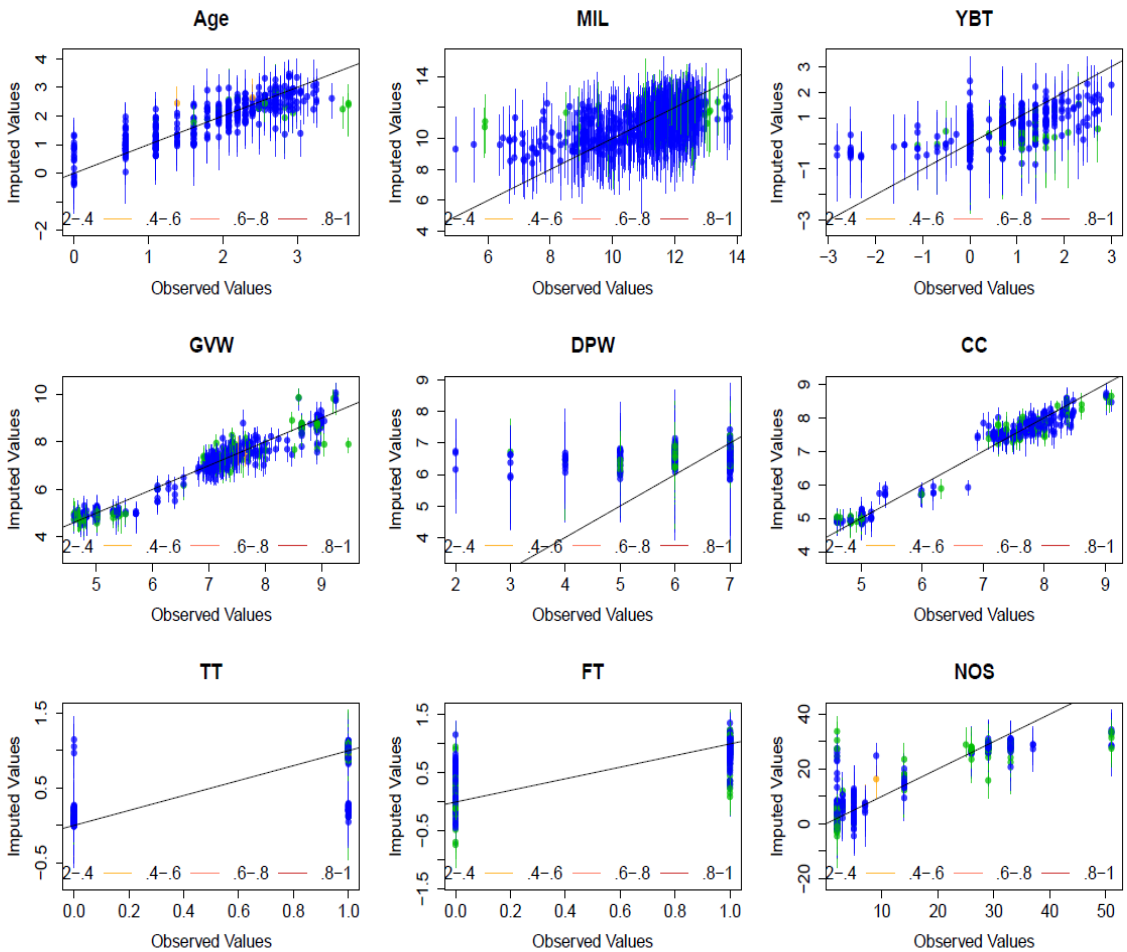


Figure 3-6: Diagnostic graph of observed variables plotted against the imputed values

3.3.4.2 ANN exploratory phase

A range of different ANN model configurations was explored in the training data set (a random 75% split of the data). The networks were confined to two layers because increasing the number of layers or the number of neurons did not improve the information criteria or MSE values. The top panel of Figure 7 depicts AIC and BIC values for the tested two-layer architecture, lower values indicating better fit. As the number of nodes in the first and second layer decreased the AIC and BIC numbers decreased. The minimal value was reached for both criteria at a NN4.1, indicating that this was the model with the lowest number of parameters while showing the highest likelihood based on the test data. Comparing the MSE values of the ANN and GLM model, the GLM model generally performed better.

The ANN models to be tested in the validation step were determined to be NN4.1 (lowest AIC, BIC and MSE in test data), NN4 (testing whether the layer with one node is needed) and NN3.1 (testing whether four nodes are needed).

Figure 3.7 shows the predictions made based on the GLM and the NN4.1 in the test data (random complementary 25% split of the data set). As the figure shows, both models identified the general distribution of the observed fuel economy data fairly well. This is also mirrored by the correlations between the observed data and the predicted values from the GLM ($r = 0.77$, $p < 0.001$), the respective correlation between observed and predicted for the ANN ($r = 0.73$, $p < .001$) and finally the correlation between the predicted values from both models ($r = 0.92$, $p < 0.001$).

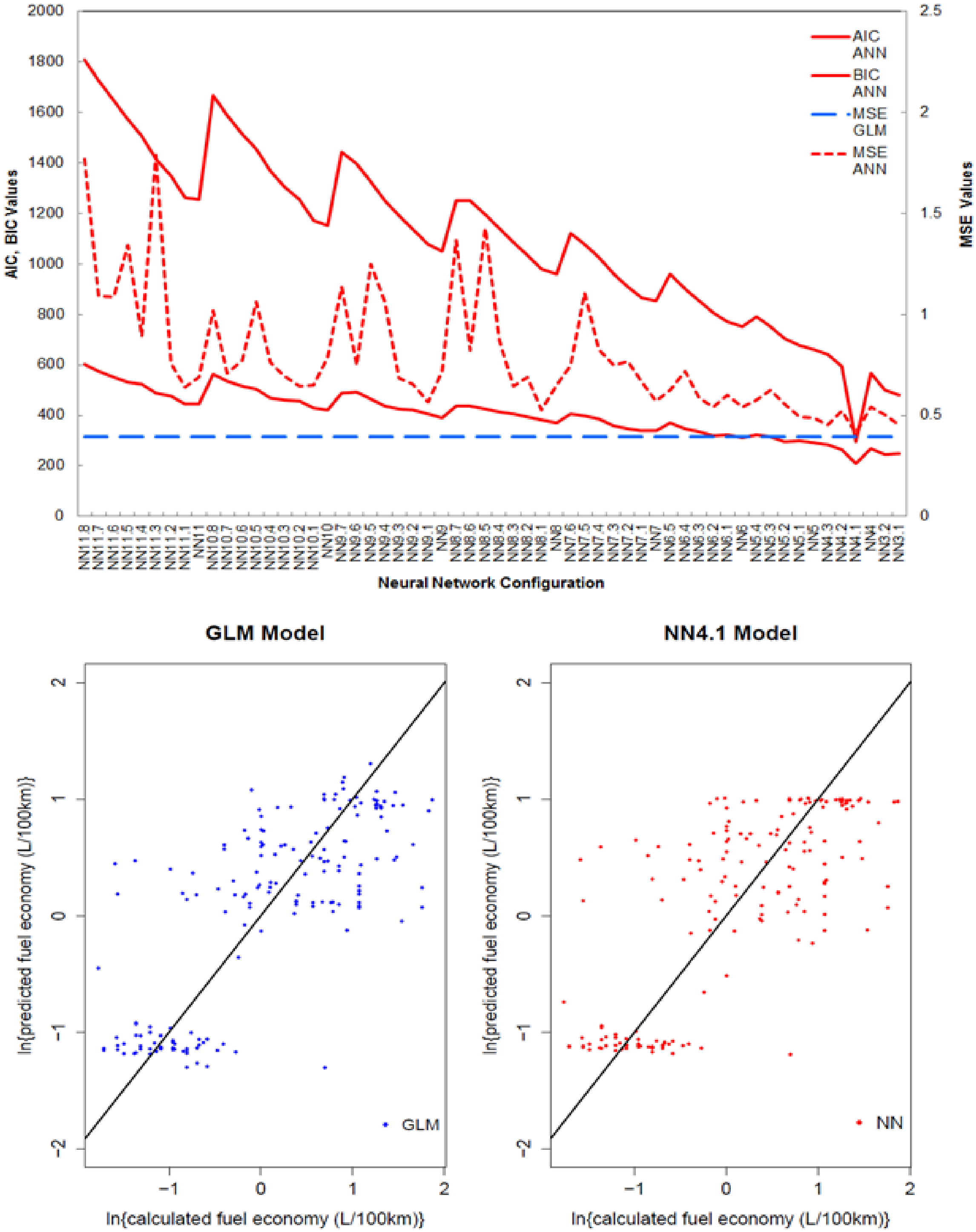


Figure 3-7: A comparison of GLM and various configurations ANN model and then the best NN model (2 layers, 4 and 1 neuron) is compared to the GLM model. NN_{ij} denotes the network configuration of the neural network with i, the number of nodes in the first layer and j the number of nodes in the second layer. All the values in these plots are log-normal transformed.

3.3.4.3 Cross validation

The results of the cross validation from the iterative bootstrap of all four models is shown in Figure 3.8. In Figure 3.8 (I-IV) shows the difference in AIC and BIC values of the originally best fitting model (NN4.1) compared to its two closest competitors (NN4, NN3.1). Positive differences in each panel indicate that NN4.1 had a worse fit in a cross-validation run (i.e. larger values than the competitor), negative differences indicate evidence against the competitor model. We can see that for both information criteria and both comparison models the overwhelming majority of differences indicates that the simpler model shows a better fit to the data than NN4.1 (NN3.1: AIC 99.7% BIC 100%; NN4: AIC 62.7% BIC 92.2%).

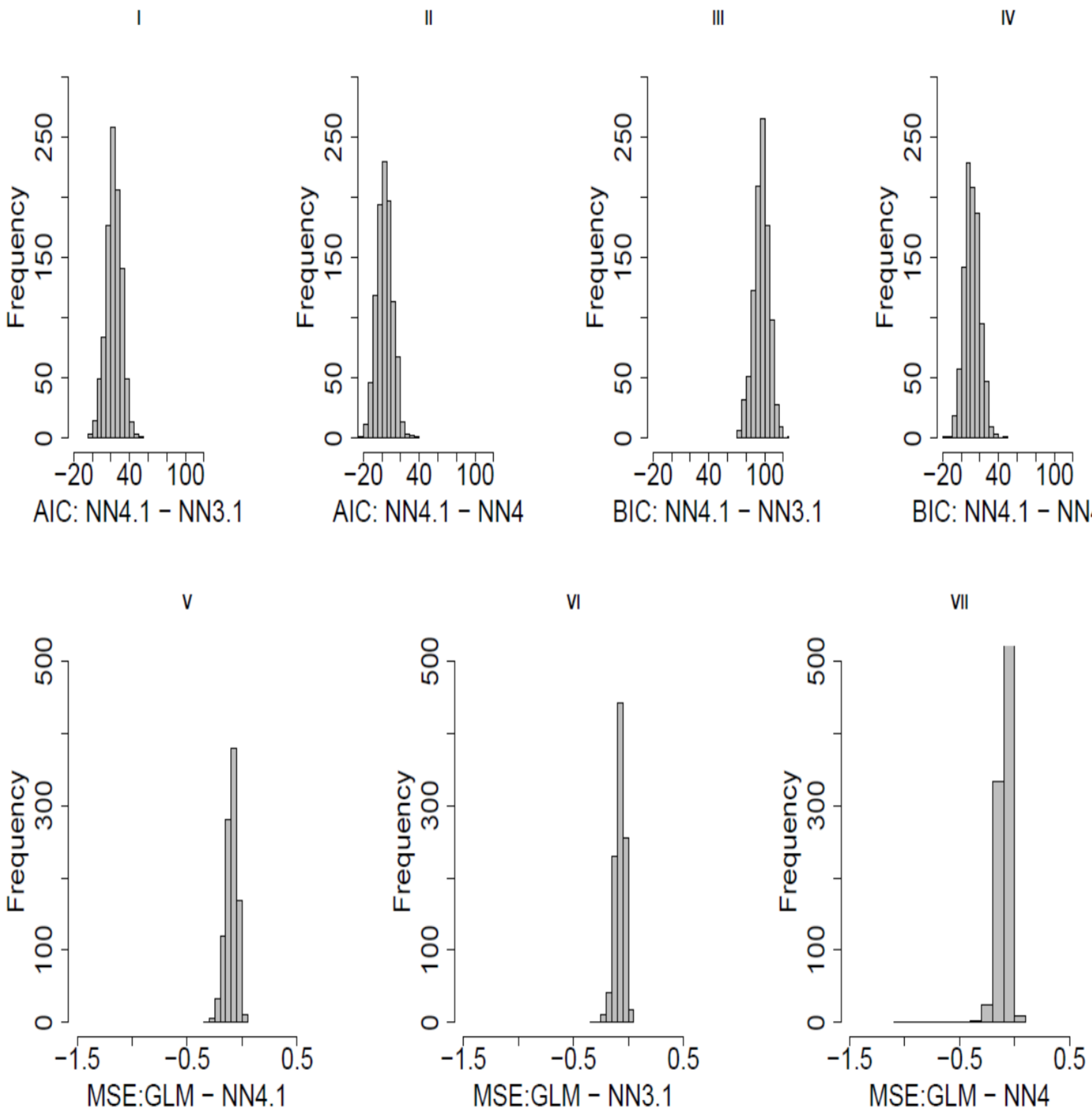


Figure 3-8 : Plot of the comparative statistics of the bootstrap. AIC, BIC, MSE of the three top ANN models (NN4.1, NN3.1, NN4) and the GLM model. I, II, III, IV comprises of AIC and BIC comparisons of ANN and V, VI, VII comprises of MSE comparisons of GLM and ANN.

V-VII of Figure 3.8 shows the difference in MSE values between the GLM predictions in training/test data splits and the three network models. Negative differences indicating that the GLM was performing better than an ANN (larger MSE for ANN and vice versa for negative ones). The GLM consistently performed better than ANN for all the models as the difference between MSE GLM values and ANN MSE values was again negative for the overwhelming majority validation runs (NN4.1 worse MSE in 99.0%; NN4 in 99.1%; NN3.1 in 98.3% of cross validation runs).

3.3.4.4 Interpretation of the GLM

Fitting the GLM to the whole data set results in a significant omnibus test statistic (Deviance=376.42, df=15, $p < 0.001$), indicating that the chosen predictors together inform fuel economy statements given by the respondents. Table 3.3 presents the estimated coefficients. Engine size is the only coefficient that is deemed significant based on the conventional nominal alpha level of $p < 0.05$: per standard deviation increase in engine size, the fuel consumption of a vehicle is increased by 0.48 standard deviations of L/100km. Three variables showed marginally significant relationships with fuel consumption, which were the weight of the vehicle (GVW), whether the vehicle was bought in Kenya (UK) and whether it was used overseas (UO), the latter two indicating that these cars consumed more fuel than the newly bought cars.

Table 3-3: Unstandardized regression coefficients of the GLM fitted to the 75% and imputed data set

Variable	Estimate	Standard Error	tvalue	Pr(>|t|)
(Intercept)	0.01	0.03	0.54	0.59
CC	0.48	0.20	2.43	0.02*
GVW	0.22	0.13	1.74	0.08.
MIL	-0.03	0.04	-0.95	0.34
Age	-0.05	0.05	-0.95	0.34
DPW	0.00	0.03	-0.10	0.92
YBT	-0.01	0.04	-0.29	0.77
NOS	0.00	0.06	-0.08	0.94
AfritypeL2e/L3e	-0.12	0.16	-0.76	0.45
AfritypeN1	-0.03	0.04	-0.67	0.50
passenger	-0.07	0.08	-0.87	0.39
FT	-0.06	0.07	-0.95	0.34
TT	0.02	0.06	0.32	0.75
NN (Missing)	0.00	0.04	0.10	0.92
UK	0.07	0.04	1.85	0.06.
UO	0.07	0.04	1.67	0.09.

The model reveals that CC (engine size of the vehicle) is the only significant predictor of fuel economy. The coefficient of [0.48] means that by increasing the engine size of a vehicle by one standard deviation (i.e. x cc), the fuel economy is increased by 0.48 SD (i.e. y L/100km). To test for collinearity amongst the predictor variables, variance inflation factors (VIF) were calculated and found to be between 5 and 10, showing high correlation between the predictor variables. CC and GVW, were in turn removed from the model and their effect analysed. Collinearity was not resolved by dropping GVW, (VIF was found to remain between 5 and 10), and it emerged on dropping GVW, FE' may also depend on AfritypeL2e/3e, fuel type (FT) and the state the vehicle was bought if new or old (NN), as the p-value <0.05. Dropping engine size (CC) increases collinearity (VIF>10), it emerged FE' may also depend on AfritypeL2e/3e and the state the vehicle was bought if new or old (NN). Complete tables of results are in the supplementary section S4 and S5.

3.4 Discussion

This study has shown that for cities such as Nairobi, with limited or low quality data and a large informal transport component (*tuktuk*, *matatu*, *bodaboda*, *Askfortransport);* questionnaire survey data can be reliably used to determine fuel economy of an urban fleet. Fuel economy models were presented; first data multiple imputations were successfully used to fill in missing data, then modelling performance of different ANN models was compared to a GLM model, where GLM model consistently performed better. In analysing the significance of the predictor variables, engine size was found to be most significant and three other variables showed significant relationships with fuel economy: weight of the vehicle (GVW), whether the vehicle was bought in Kenya (UK) and whether it was used overseas (UO). There were however constraints due to the sample size in two ways: firstly, the total sample disaggregated to vehicle categories for heavy goods vehicles (HGVs) for example reduced the sample to N=10 (see table 2), affecting the level of confidence of the results in this category. This is because the trucks and lorries are kept out of the city centre and replaced with smaller trucks, hence their sample was much smaller than that for the passenger vehicles. Secondly, there was the problem of collinearity detected amongst the predictor variables, for example between weight of the vehicle and engine size. However, removing these highly correlated variables from the model did not show improvement in the collinearity. Given the constraints on the sample size resulting from disaggregation and the missing variables in the sample, elimination of those variables which may have reduced collinearity would have resulted in a much smaller sample size and so this was not carried out. However even with this limitations, we can conclude fuel economy and vehicle activity developed for formal transport in developed countries sectors do not map the complexity of the informal sector in developing countries due to differences in vehicle types and utility of the vehicles.

3.4.1 Comparison with previous studies

Major vehicle manufacturers (Japan, USA, EU and China) have fuel economy policies (Plotkin, 2016). Figure 3.9 compares the various studies conducted to estimate vehicle fleet fuel economy compared to the current fuel economy values of this study. The Kenyan passenger cars have 3 times poorer/lower fuel economy compared to the Japanese, EU and Indian fleets and 2 times lower than the South Africa, Chinese and USA fleets. For the Kenyan light duty commercial vehicles, fuel economy was up to 3 times poorer compared to the Japanese fleet or targets. Fuel economy of the two-wheelers and three-wheelers of the Kenyan fleet (named *bodaboda* and *tuktuk* respectively) were two times poorer than the Indian Fleet. The *matatu* 14 seater was determined to be the equivalent to the Japanese small bus (vehicle designed to carry 11 or more passengers and with GVW up to 3500 kg) and the South African minibus taxi. In this category the Japanese fleet was 2 times and South Africa fleet was 1.7 times more fuel economic than the *matatu* 14 seater.

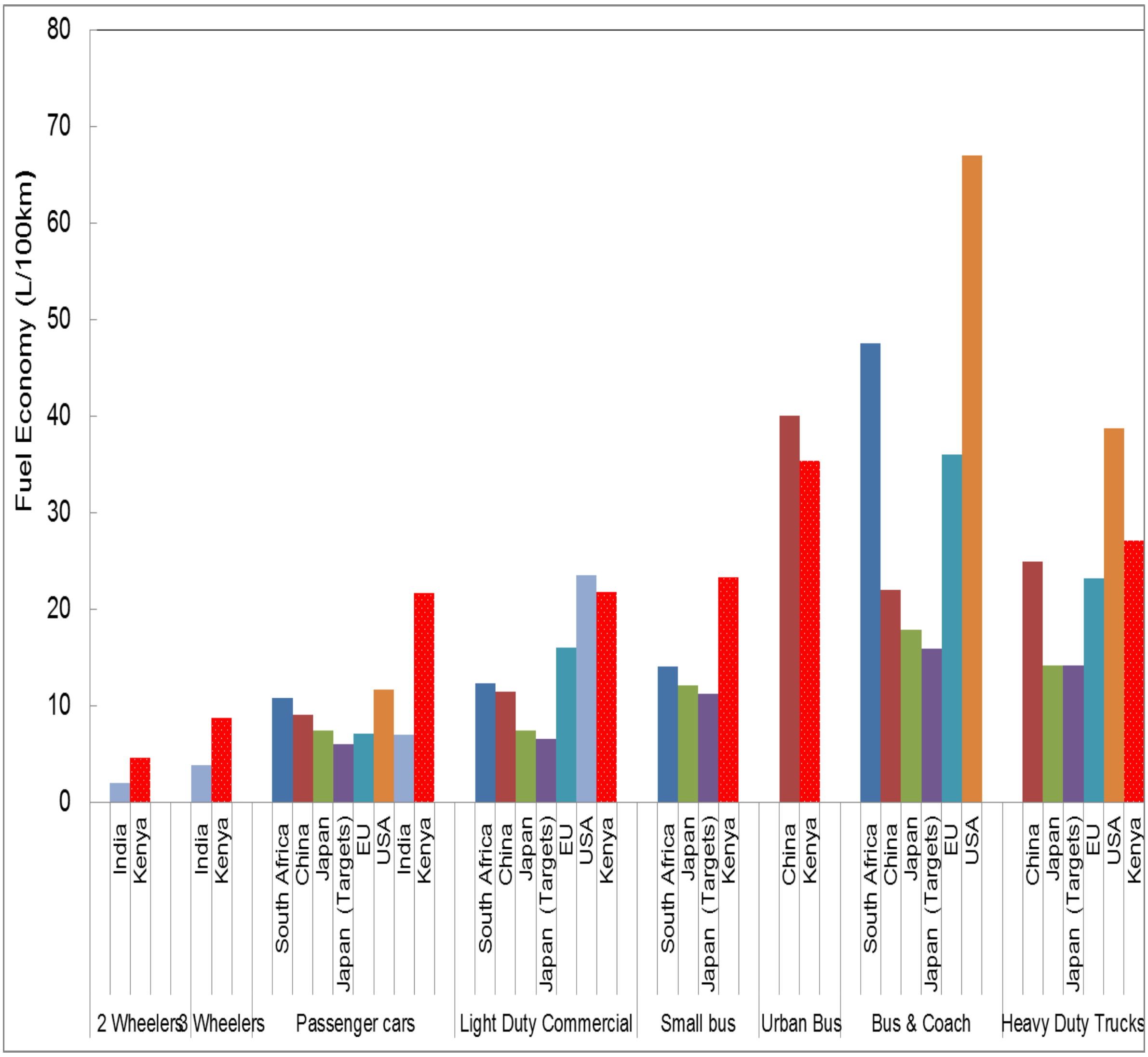


Figure 3-9: Fuel economies for different countries from various sources: India (Goel *et al.*, 2015), Kenya (current study), South Africa (Venter and Mohammed, 2013), China (Huo *et al.*, 2012), Japan (JAMA, 2016), EU (Law *et al.*, 2011; Ntziachristos *et al.*, 2014), USA (Law *et al.*, 2011; EPA, 2014).

In Kenya, 90% all imported and registered light duty vehicles between 2010-2012 were from Japan and Europe (ERC, 2015b). Japan has very stringent fuel economy standards to meet their 2015 targets (JAMA, 2016) , yet when the Kenyan fleet is compared to the Japan in-use vehicle fleet in 2004, overall fleet fuel economy was 2 to 3 times worse. The comparison in Figure 3.9 is made on the assumption that other studies have similar or smaller confidence intervals. The confidence interval for the Kenyan study (see Figure 3.4), ranges from 7-54% with an average of 24%.

The passenger fuel economy for USA includes light duty trucks (EPA, 2014), while for other countries light duty trucks were a separate category. This may contribute to the seemingly poor fleet fuel economy for passenger cars in the USA, even when the technology and fuels meet the latest equivalent current European and Japanese standards.

The light duty commercial fleet in-use in Nairobi was typically *AskforTransport* vans and trucks, an informal van and truck hire within the city and in residential areas. This category had the second highest age, as “retired” older vehicles are not scrapped but are repurposed. The fuel economy of this category is better than USA fuel economy for the same category, but USA fleet for this category is heavier (weight of this category in USA includes trucks up to 3 800 kg, whilst the other fleets are less than 3 500 kg) and bigger engines (EPA, 2014; Plotkin, 2016).

Bodabodas and *tuktuks* are mainly imported from Asia: India, Indonesia, Thailand, and China as they are cheaper compared to European imports (Assamoi and Liousse, 2010; Kumar, 2011). Motorcycles are used as public transport in India and Vietnam as they are in Kenya, but they have twice the average mileage compared to Kenya, 79.7± 4.3 km/day (Oanh *et al.*, 2012; Goel *et al.*, 2015) . In Asian cities they have a lower daily mileage because they represent a larger share of the urban vehicle fleet, the reason being that motorcycles are often used in cities to avoid congestion, for instance motorcycles represent 90% of the vehicle fleet in Hanoi (Oanh *et al.*, 2012). Kenyan motorcycles were in this study (see Figure 3) found to be mainly 150cc engine and 4-stroke engine compared to motorcycles in West Africa that are 50cc engines and two stroke (Assamoi and Liousse, 2010). Given the trend in increasing numbers of motorcycles in SSA (Assamoi and Liousse, 2010; Kumar, 2011), the average daily mileage for motorcycles may also decrease. The study also highlighted high intensity vehicle usage, indicated by an average vehicle mileage, VKT, for other vehicle types such as passenger cars (61.04±7.18 km/day), and *matatu* 151.55±10.42 km/day.

South Africa has a strong domestic vehicle manufacturing industry and restricts imports of second-hand cars (UNEP, 2015) and is therefore unlike Kenya where 99% of vehicles are second-hand (ERC, 2015b). Their vehicles perform better than Kenya's, though reliable minibus taxi data (equivalent to *matatu*) is often not available (Behrens *et al.*, 2017). Kenyan *matatu* 14 seaters are old (16.9±0.2 years) and are originally 9 seater vans being converted into 14 seater; overloading and aged component of the fleet; this likely accounts for the poorer fuel economy compared to South Africa. The bigger *matatus,* equivalent to urban buses, are relatively new and have a better fuel economy comparable to the Chinese fleet. However with expected vehicle technology deterioration (Chiang *et al.*, 2008) further aggravated by poor road conditions, low fuel quality and lack of inspection and maintenance (I/M) programmes this advantage in fuel economy may not be maintained.

The age of the vehicle is normally an indicator of the emission control technology and hence emissions from the vehicle (Zachariadis *et al.*, 2001; Goel *et al.*, 2015). This may hold true for countries that enforce emission compliance checks when importing vehicles and have regular I/M programs (Pillot *et al.*, 2014). Imported vehicles with emissions control technology often have these removed or they malfunction without an enforceable I/M program (Pillot *et al.*, 2014). The vehicle fleet average age is often high in Kenya: *bodaboda* 2.69±0.38 years, passenger cars 11.1±0.57 years, *matatu* 8.80±1.24 years. However, age may not to be a good indicator for emission technology on light duty vehicles in Kenya as a previous study (Lents *et al.*, 2004) has shown. This is because in Lents et al., (2004), the vehicles had the required technology but the fuel quality (unleaded petrol) required did not meet standards for emission reduction devices (catalytic converters) to function. Age is also not a good indicator for the technology of emission reduction on HDVs as the original equipment manufacturers (OEMs) are not responsible for the final vehicle configuration other than the powertrain, chassis and cab (Hill *et al.*, 2011). This is supported by the findings of this study of a significant variance in the age of HDV (75%), shown in Figure 3.3: AfritypeM3C and AfritypeN2 differ by 118% and 105 % respectively. In Kenya most HDV, such as trucks, are imported as engine chassis and cab and built in the country for various uses: *matatus*, buses and heavy commercial trucks. However the sample size for the HDVs for this study was limited, this is because HDVs (trucks and lorries) have limited geographical areas of circulation in Nairobi. Thus the HDV variance should be viewed cautiously until further studies are conducted with a bigger sample size.

Comparing FE values from different parts of the world is rather uncertain. The studies from which data were compared had both diesel and petrol vehicles of similar capacity, mass and power specifications. However, identical average properties were not possible for some countries (for example the USA) due to different categories for vehicle weight and engine size. Even when vehicles had identical properties to fleets in other parts of the world, their utility especially those of the informal sector were different. To overcome this challenge, developing country fleets (India, South Africa and Thailand) were sought for comparison as their fleets included an informal sector and had similarity in utility. The informal transport sector in SSA is usually poor organization and the industry is often deregulated unlike Asia (Assamoi and Liousse, 2010; Kumar, 2011; Goel *et al.*, 2015). The methods to measure FE also differed; real-world exhaust measurement were sought as these were deemed to be most accurate (Huo *et al.*, 2011; Franco *et al.*, 2013; EPA, 2014; JAMA, 2016) but few such studies are undertaken, thus other in-use vehicle studies were also included (Law *et al.*, 2011; Venter and Mohammed, 2013; Goel *et al.*, 2015). The year the study was undertaken may also have contributed to the uncertainty as that may change the technology the vehicles may have and the fuel quality. To reduce this effect, the comparator studies were limited to years between 2010-2015. Furthermore, fuel consumption becomes extremely high under traffic congestion (Wang *et al.*, 2008; Zhang, Wu, Liu, Ruikun, *et al.*, 2014) which is a severe and worsening reality in Nairobi, like in most developing cities (Gyimesi *et al.*, 2011; Kinney *et al.*, 2011;

Salon and Aligula, 2012; Petkova *et al.*, 2013; UN-HABITAT, 2014). Therefore traffic congestion ought to be factored into FE studies, often this is not the case (Smit *et al.*, 2008). However even with these limitations, we can conclude vehicle activity and thus fuel economy developed for formal transport sectors does not map the complexity of the informal sector due to different vehicle types and utility of the vehicles.

3.4.2 Imputation

Multiple imputation of incomplete multivariate data was successfully applied to the vehicle fleet data. The diagnostics of the imputation in Figure 3.6 shows around 90% of the confidence intervals for the variables CC, GVW, Age, MIL, DPW, YBT, TT, FT and NOS contain the y = x line, which means that the true observed value falls within this range, and therefore the imputation was effective in predicting the missing values. The result of the imputation is a bigger data complement than if only those observations for which every variable measured were to be included. The imputation for Engine Size (CC) was a better imputation than Days per Week (DPW). Engine size of the vehicle was verifiable through second-hand vehicle websites and linked to other variables such as GVW, transmission, type of fuel and number of seats. Also the number of times a vehicle is driven per week (DPW) may be strongly linked to variables not sought after in the questionnaire such as type of job, distance from home or work, fuel price change.

The map of the missing values in Figure 3.5 shows the variable Age has the most missing values. This is because during the interviews, if the driver of the vehicle was not the owner, they often did not have the vehicle logbook, thus the age of vehicle, when the vehicle was bought, engine size and weight was not verifiable on site. Secondary data from vehicle sales website were used to verify and supplement this information where possible. A previous traffic survey in Nairobi was not able to directly ascertain the age of the vehicle and relied on odometer readings as a proxy for the age of vehicles the (UC Riverside, 2002). This is because at the time vehicle imports were restricted to new vehicles so this proxy worked, in 2015, 99% of vehicles imported are second-hand (ERC, 2015b). MIL, which is the odometer reading, had the second highest missing values. Drivers of *bodabodas*, *tuktuks, matatus* and taxis openly admitted to tampering with the odometers, this finding was supported by a previous study which had very low mileage from a multiple regression methodology to determine average mileage, and concluded that tampering had occurred (UC Riverside, 2002). Engine size (CC) and GVW were still verifiable *via* websites thus the missing values were less in the original dataset before the imputation.

3.4.3 Fuel Economy Model

In assessing the comparative statistics in Figure 8, the GLM model consistently performed better than ANN model, engine size was deemed to be most significant in predicting FE.

We chose a cross-validation approach to guard our predictor selection approach against over-fitting (Arlot and Celisse, 2010; Slavin *et al.*, 2013; Alice, 2015). The cross-validation procedure supports our analysis with regards to this goal in three ways. First, the use of information criteria (AIC, BIC) uses indices that provide a numerical summary that takes into account both the fit to the observed data as well as the number of parameters (here layers of the ANN). Unduly complex models were therefore penalised and less likely to end up in our final set of potential models (NN4, NN4.1, NN3.1). Secondly, the use of the MSE in a test sample ensures that if a model is prone to over-fitting the training dataset it will produce worse MSEs in this sample and would again be less likely to be selected. Thirdly, running this analysis as a bootstrap (included repeated multiple imputation of missing data adding further robustness) allows us to compare the potential for over/fitting as well as adequate fit in one go. Figure 3.7 shows that the overwhelming majority of the bootstrap runs actually support the fit of simpler neural networks than NN4.1 (NN3.1: AIC in 99.7% and BIC in 100% of runs; NN4: AIC 62.7% BIC 92.2%, respectively) and the MSE supported the GLM consistently (NN4.1 worse than MSE in 99.0%; NN4 in 99.1%; NN3.1 in 98.3% of cross validation runs). The modelling performance and prediction of the GLM achieved higher accuracy, this finding is contrary to a fuel economy study that compared regression models to ANN, ANN model achieved higher accuracy (Slavin *et al.*, 2013). This may be because the success of the ANN relies on reliable input and output data to train the algorithm and bigger datasets are better for ANN model precision in prediction for instance Slavin *et al*., (2013) and Alice *et al*., (2015). Limited and incomplete vehicle fleet data is often a challenge in SSA , so while ANN is a powerful tool in modelling complex relations and systems (Goh, 1995; Slavin *et al.*, 2013; Molaie *et al.*, 2014), due to the smaller dataset it was not the better predictive model when compared to GLM model.

Engine size was deemed to be most significant although three other variables also showed significant relationships with fuel economy: weight of the vehicle (GVW), whether the vehicle was bought in Kenya (UK) and whether it was used overseas (UO), the latter two indicating that these cars consumed more fuel than the newly bought cars. Thus the study was able to identify aspects of the vehicle fleet character (especially engine size and weight of the vehicle) are key to predicting fuel economy changes, thus providing a focus on those parameters that are vital to obtain while conducting questionnaire surveys in order to derive an accurate estimate of fleet fuel economy.

3.5 Conclusion

This paper presents a novel methodology that develops a questionnaire and uses the survey data from the questionnaire to develop models to estimate in-use vehicle fleet fuel economy for cities with limited or low quality data, and that have a large informal transport fleet, such as Nairobi. The vehicle fleets FE in NMR was determined to be 2-3 times worse compared with Japan, Europe, India and China, for example, for the Kenyan passenger vehicles to meet the Japanese fuel economy targets of 5.95 L/100km would require almost a 4-fold improvement in the Kenyan FE. FE models were presented that were based on survey questionnaire data; first data multiple imputations were successfully used to fill in missing data, then modelling performance of different ANN models were compared to a GLM model. The GLM model consistently performed better than the ANN model. Engine size was deemed to be most significant factor in predicting FE.

In cities such as Nairobi that are experiencing a rapid growth in transport emissions, predicting fuel economy changes in response to changes in vehicle characteristics and activity can help inform effective transport policies that rely on the availability of robust data and the application of sound assessment methods. A baseline measure of fuel economy for both the formal and informal vehicle fleet in NMR has now been established for 2015. This identifies the substantial contribution the informal vehicle fleet is currently making to the air pollution and GHG burden. This is particularly important given the trends in this fleet component which suggest a continued increase in size of this informal transport sector with no new regulations. Application of these methods can help identify the rise of informal transport as a particularly polluting component of the transport sector and help target fuel economy improvements in changing vehicle fleets in the future. It also identifies the need to take further action to address informal transport from an air quality management and GHG emission perspective. Furthermore, vehicle activity data presented here would improve the Kenya's NDC formulation for the transport sector.

Ultimately, this will aid sustainable road transport policy implementation, which will lead to a reduction in fuel consumption and improvement of FE, leading tor reductions in GHGs emissions and improvements in air quality.

3.6 Acknowledgements

We thank the Stockholm Environment Institute (SEI) at University of York for financial support for the field work, along with *the Faculty for the Future foundation*, Schlumberger foundation for a PhD fellowship. We are grateful for the valuable input from Dr Keiko Hirota on Japanese fuel economy standards.

3.7 Supplementary

Questionnaire to determine vehicle kilometres travelled (VKT) and average fuel consumption

Date		Time		Location		Interviewer		Code	

Do you live in Nairobi?	Yes	No

*If No, thank and terminate

Where do you live in Nairobi?		Sex	M	F	Age	

No. of persons living in the respondents household		Do you own private cars?	Yes	No	If Yes, how many cars are there in your household?	

How do you travel to work?	Car (alone)	Car (with others)	Bus	Matatu	Motorbike	Bicycle	Walk	Train	Other	Work at home	No work

Do you own a motorbike?	Yes	No	Do you use a motorbike?	Yes	No	Do you own a bicycle?	Yes	No	Do you use a bicycle?	Yes	No

*Only proceed to the next question if the respondent is in/on a motor vehicle, otherwise thank and terminate.

No. of people in the vehicle including the driver		Licence Plate No.	

Type of vehicle		Fuel type		Manufacturer	
Model of the vehicle		Transmission Type (manual/automatic)		Engine size (Litres)	
Gross weight (GVW in kg)		Odometer reading (Total mileage)		Year of Manufacture	

Do you own or regularly drive this vehicle?	Yes	No

*Terminate interview if they do not own or regularly drive vehicle

How many days in a week do you use the vehicle(s)?	Veh 1	days/week	Veh 2	days/week
What is the average distance the vehicles(s) travel per day?	Veh 1	km/day	Veh 2	km/day
How many years ago was the vehicle(s) bought?	Veh 1	years	Veh 2	years

When Veh 1 was bought was it?	New		Used car overseas		Used car Kenya	
When Veh 2 was bought was it?	New		Used car Overseas		Used car Kenya	

In about how many years will the vehicle(s) be sold?	Veh 1	yrs	Never	Veh 2	yrs	Never

How much do you spend on fuel for the vehicles(s) per month				Ksh	/Month
Is the combined income of your household per month.....? (Read the income range until respondent chooses one)					
< Ksh 50 000		Ksh 100 000- Ksh 200 000		> ksh 400 000	
Ksh 50 000-Ksh 100 000		Ksh 200 000-Ksh 400 000		Refused	

*Thank you very much for completing the survey! And for validation purposes, may I please have your first name?
Name: Additional comment:

Figure S 1: A sample questionnaire for use in the field survey in Nairobi

Table S 1: A table of the implausible data excluded following the data screening and verification step in 2.6

Model	TT	Engine_size_CC	GVW	Odometer.Reading	Yr_Man	Age_of_vehicle	Vehicle_ownership	Days_per_week	AvDista_perDay	Yrs_Bought	New_Used	SpendFuel_Kshmonth	No_of_Seats	L_per_month	L_per_day	L_per_km	L_per_100km	Afritype
NZE	AUTOMAT	1300	1200	78502	2006	9	YES	4	150	NA	UO	12000	5	128.631	4.2877	0.0286	2.858	AfritypeM1B
TOYOTAE1	MANUAL	2000	1095	202957	2002	13	YES	7	10	1	UK	60000	5	643.156	21.439	2.1439	214.4	AfritypeM1C
CARIB	AUTOMAT	1600	1100	180000	1997	18	YES	4	350	2	UK	9000	5	96.4734	3.2158	0.0092	0.919	AfritypeM1C
VOXY	AUTOMAT	2000	1580	96430	2005	10	YES	7	300	2	UO	10800	5	115.768	3.8589	0.0129	1.286	AfritypeM1C
VOXY	AUTOMAT	2000	1500	NA	2006	9	YES	7	7	5	UO	30000	5	321.578	10.719	1.5313	153.1	AfritypeM1C
LANDCRUI	AUTOMAT	4500	2600	92282	2000	15	YES	7	10	1	NN	112000	5	1200.56	40.019	4.0019	400.2	AfritypeM1D
KLUGER V	AUTOMAT	2400	1716	84000	2005	10	YES	7	10	2	UO	30000	5	321.578	10.719	1.0719	107.2	AfritypeM1D
RANGER	MANUAL	3200	1900	20430	2013	2	YES	2	300	1	NN	9000	5	109.184	3.6395	0.0121	1.213	AfritypeM1D
PICKUP	MANUAL	NA	NA	NA	NA	NA	YES	7	30	NA		120000	2	1455.78	48.526	1.6175	161.8	AfritypeN1
QD	MANUAL	2200	1650	54100	NA	NA	YES	7	550	NA		75000	14	909.863	30.329	0.0551	5.514	AfriypeM2
CARAVAN	MANUAL	1600	2660	322940	1998	17	YES	7	14	NA	UO	56000	14	679.364	22.645	1.6175	161.8	AfritypeM2
TD-27	MANUAL	2500	1650	NA	1989	26	YES	7	15	2	UK	63000	14	764.285	25.476	1.6984	169.8	AfritypeM2
TIGER	MANUAL	150	175	65123	2014	1	YES	6	400	1	NN	10400	2	111.48	3.716	0.0093	0.929	AfritypeL3e
TVS-ES	MANUAL	100	120	74640	2011	4	YES	6	100	3	NN	60000	2	643.156	21.439	0.2144	21.44	AfritypeL3e
BOXER	MANUAL	100	109	NA	NA	NA	YES	6	500	4	NN	6000	2	64.3156	2.1439	0.0043	0.429	AfritypeL3e
PATHFIND	AUTOMAT	3000	2700	15004	2013	2	YES	7	4	1.5	NN	27200	5	329.977	10.999	2.7498	275	AfritypeM1D
PRADO TX	AUTOMAT	3000	2025	83527	2004	11	YES	5	5	1	NN	25000	5	267.982	8.9327	1.7865	178.7	AfritypeM1D
TOYOTA G	AUTOMAT	2500	1575	200648			YES	7	10	7	UO	30000	5	363.945	12.132	1.2132	121.3	AfritypeM1D
SURF	MANUAL	2400	1890	238742	1998	17	YES	7	10	11	NN	30000	5	363.945	12.132	1.2132	121.3	AfritypeM1D

Table S2: A table of Afritype vehicle classes tests on significant differences between the means of the calculated fuel economy (FE') before imputation of the dataset. P <2.2e^{-16} for N = 707.

Variable	Estimate	Standard Error	t stat	P value
(Intercept)	8.73	4.61	1.90	0.06
AfritypeL3e	-4.18	4.75	-0.88	0.38
AfritypeM1C	10.08	4.85	2.08	0.04
AfritypeM1D	31.91	5.17	6.17	< 0.001
AfritypeM2	14.47	5.06	2.86	< 0.001
AfritypeM3A	28.66	5.89	4.86	< 0.001
AfritypeM3B	27.29	4.87	5.60	< 0.001
AfritypeM3C	23.75	7.98	2.98	< 0.001
AfritypeN1	13.00	5.35	2.43	0.02
AfritypeN2	18.33	6.14	2.98	< 0.001
AfriypeM1B	7.26	6.01	1.21	0.23

Variable	Estimate	Standard Error	t stat	P value
(Intercept)	30.11	3.92	7.69	< 0.001
ASKP	-9.58	4.49	-2.13	0.03
BOD	-25.55	4.02	-6.35	< 0.001
CCAR	-19.24	5.54	-3.47	< 0.001
MAT	1.88	4.03	0.47	0.64
MBK	-26.04	5.98	-4.35	< 0.001
PKP	-14.63	6.45	-2.27	0.02
PRIV	-5.49	4.06	-1.35	0.18
TAXI	-20.13	4.68	-4.30	< 0.001
TUK	-21.38	5.34	-4.01	< 0.001

Table S3: A table of GLM model results with GVW dropped from the data set to test for collinearity effect

Variable	Coefficent	Standard Error	tstat	Pvalue
(Intercept)	1.03	0.19	5.48	< 0.001
CC	0.10	0.05	2.16	0.03
MIL	-0.02	0.04	-0.36	0.72
Age	0.00	0.01	-0.04	0.97
DPW	0.03	0.03	1.17	0.24
YBT	-0.03	0.03	-1.05	0.29
NOS	0.14	0.06	2.51	0.01
AfritypeL2e/3e	-0.99	0.19	-5.14	< 0.001
AfritypeN1	-0.14	0.17	-0.81	0.42
passenger	-0.03	0.19	-0.15	0.88
FT	-0.38	0.12	-3.18	< 0.001
TT	-0.38	0.15	-2.48	0.01
NN (missing)	0.58	0.12	4.71	< 0.001
UK	0.08	0.08	0.95	0.34
UO	-0.26	0.11	-2.29	0.02

Variable	Coefficent	Standard Error	tstat	Pvalue
(Intercept)	0.94	0.20	4.67	< 0.001
GVW	0.29	0.13	2.26	0.02
MIL	0.00	0.01	-0.05	0.96
Age	0.00	0.01	0.19	0.85
DPW	0.04	0.03	1.33	0.18
YBT	-0.02	0.03	-0.83	0.41
NOS	0.05	0.07	0.62	0.53
AfritypeL2e/3e	-0.78	0.23	-3.40	0.00
AfritypeN1	-0.11	0.16	-0.68	0.49
passenger	-0.06	0.20	-0.32	0.75
FT	-0.32	0.13	-2.46	0.01
TT	-0.39	0.16	-2.51	0.01
NN (missing)	0.59	0.12	4.86	< 0.001
UK	0.10	0.08	1.15	0.25
UO	-0.25	0.11	-2.20	0.03

Chapter 4

The work outlined in this chapter has been adapted from a research paper prepared for publication. I undertook all data analysis, but Dr Harry Vallack and Dr Chris Malley provided insight into the calculation of the inventories for non-transport sector emissions. Professor Mike R. Ashmore, Dr Chris Malley and my supervisors, Dr Lisa Emberson, Dr Harry Vallack and Dr Dietrich Schwela following an initial draft, made valuable contribution to the presentation of results through discussions and manuscript editing. Their editing of the article upon which this chapter is based improved the accurateness of the inventories and the policy relevance of this work.

4 Assessment of the impact of road transport policies on air pollution and greenhouse gas emissions in Kenya.

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Abstract

Reducing emissions to the atmosphere of air pollutants, and greenhouse gases (GHGs) in sub-Saharan African (SSA) countries could substantially benefit human health, and reduce the contribution of SSA countries to climate change. The contribution of road transport to air pollution and GHG emissions is growing substantially across SSA. However, lack of regulation in many SSA countries means that the magnitude of current road transport emissions are poorly estimated, and the potential emission reductions and associated benefits from the implementation of mitigation strategies have not been extensively explored. Kenya is an example of one such country where the options for reducing road transport emissions are not well understood. The aim of this work is therefore to i) estimate air pollutant and GHG emissions from the road transport sector between 2010 and 2050, projected based on estimated changes in the vehicle fleet across Kenya, ii) place current (i.e. 2010) road transport emissions in the context of emissions from all other major source sectors in Kenya, and iii) estimate the road transport emission reductions that could result from the implementation of different mitigation strategies. We therefore compiled a detailed 'bottom up' transport emission inventory for Kenya for 11 air pollutants and greenhouse gases. In 2010, road transport emissions accounted for 61% of total nitrogen oxides (NO_X) emissions in Kenya, 39% of fine particulate matter ($PM_{2.5}$), 20% of carbon dioxide (CO_2), 19% of non-methane volatile organic compounds (NMVOC) and 7% of black carbon (BC) emissions. In the business as usual (BAU) scenario road transport emissions increases from 4 to 31-fold by 2050, motorcycles account for nearly all pollutants. Improved vehicle emission and fuel economy standards, fuel shift to CNG and investment in public transport are all shown to be effective road transport mitigation options that would support Kenya's climate change goals with the additional benefits of better air quality and improved health. For example, full implementation of vehicle emissions standards equivalent to Euro IV standards and attainment of Japanese 2015 fuel economy standards by 2050 in Kenya was estimated to reduce road transport CO_2 emissions by 61%, 93% for BC and 65% for NO_X.

Keywords:

Vehicle, Emissions, GHG, Transport, SLCP, SSA, inventories, air pollution

4.1 Introduction

The road transport sector is a major contributor to outdoor air pollution, including elevated concentrations of ground-level ozone (O_3), fine particulate matter ($PM_{2.5}$) including black carbon (BC), and nitrogen oxides (NO_X) and to greenhouse gas (GHG) emissions, thereby affecting human health, agricultural productivity and climate (Van Dingenen *et al.*, 2009; Shindell *et al.*, 2011; Stohl *et al.*, 2015; Li *et al.*, 2016; Klimont *et al.*, 2017; Susan C. Anenberg *et al.*, 2017). Globally, the road transport sector is a major emission source of NO_X, and primary $PM_{2.5}$ emissions (Bond *et al.*, 2004; Streets *et al.*, 2004; Shindell *et al.*, 2011, 2012; UNEP, 2011). Vehicles also contribute to other gaseous and particulate emissions including carbon monoxide (CO), sulphur dioxide (SO_2), non-methane volatile organic compounds (NMVOCs), ammonia (NH_3), black carbon (BC), organic carbon (OC), and greenhouse gases (GHGs) such as carbon dioxide (CO_2), methane (CH_4) and nitrous oxide (N_2O) (Goel and Guttikunda, 2015; Kishimoto *et al.*, 2017). These emissions contribute to secondary formation of ground-level ozone (NO_X, NMVOC, CH_4 and CO), and secondary $PM_{2.5}$ (NO_X, SO_2 and NH_3), with resulting impacts on human health and climate (Shindell *et al.*, 2011).

For Africa, previous emission estimates have identified transport as an important source of NO_X, CO, BC and NMVOC emissions (Assamoi and Liousse, 2010; Liousse *et al.*, 2014; Marais and Wiedinmyer, 2016). These regional emission inventories highlight historical increase in road transport emissions across Africa, as well as the potential for substantially larger increases in the future, which is projected to increase air pollution health burdens in this region (Assamoi and Liousse, 2010; Doumbia *et al.*, 2012; Liousse *et al.*, 2014; Mapako *et al.*, 2015; Marais and Wiedinmyer, 2016; Lacey *et al.*, 2017). For example, in SSA in 2030 it is estimated that over 20 000 deaths attributable to air pollution from road transport emissions will occur in the scenario without future vehicle emissions control (Shindell *et al.*, 2011). However, while these estimates have been conducted at the continental scale, there is a lack of analyses at the national level that evaluate the current state of road transport emissions, projected changes into the future and the likely effective of mitigation measures in individual African countries.

In sub-Saharan Africa (SSA), vehicle ownership, especially in cities, has increased because of rapid economic growth, collapse of formal public transport, and increasing urbanization coupled with increase in gross domestic product (GDP) per capita (Assamoi and Liousse, 2010; Pirie, 2013). In addition to the increasing number of vehicles, emissions from road transport are exacerbated by: the high average age of the fleet which is mainly composed of imported second-hand vehicles (accounting for ~90% of vehicles in SSA (Assamoi and Liousse, 2010; Odhiambo *et al.*, 2010; Kumar, 2011; Gaita *et al.*, 2014; Liousse *et al.*, 2014)), poor fuel quality, poorly maintained roads, lack of vehicle emission regulations and inadequate implementation of vehicle inspection and maintenance programmes (Zachariadis *et al.*, 2001; Lents *et al.*, 2004; van Vliet and Kinney, 2007; Schwela, 2012; Pirie, 2013; Randu, 2013; Marais and Wiedinmyer, 2016). There has also been a rapid increase in the use of informal public transport vehicles (Behrens *et al.*, 2017), for which emissions have not been quantified (Aduagba *et al.*, 2013; Liousse *et al.*, 2014). Combined with often inconsistent vehicle registration, there is currently a large knowledge gap when attempting to quantify air pollution and greenhouse gas emissions (Assamoi and Liousse, 2010; Liousse *et al.*, 2014). Therefore national transport emission inventories are needed to design and evaluate suitable policies to mitigate air pollution, that take account of the specific social and policy contexts for road transport within each country (Ramachandra and Shwetmala, 2009). This study will therefore focus on Kenya's road transport sector, where many of the factors described above also affect the road transport fleet, and associated air pollution and climate change-relevant emissions.

In Kenya, road transport is the dominant mode of transport and carries 93% of all freight and passenger traffic (Gachanja, 2012). Public transport is dominated by *matatus* (minibus shared taxis) and *Bodaboda* (motorcycles) (Ministry of Transport Kenya, 2011;

Gachanja, 2012; Ommeh *et al.*, 2015; Behrens *et al.*, 2017) and freight is dominated by heavy duty trucks which also serve neighbouring landlocked countries (Government of Kenya, 2012). The total number of vehicles has increased nearly four-fold since 1998 (KNBS, 2013b, 2014b). The vehicle fleet in-use is poorly serviced and old (Kinney *et al.*, 2011), and the share of second-hand imported vehicles has grown to ~99% of all vehicle imports (Lents *et al.*, 2005; ERC, 2015b). The majority of the vehicles are imported from Japan, for example, 87% of light duty vehicles between 2010-2012 were imported from Japan (ERC, 2015b) with Kenya having an 8 year age limit for vehicle importation (Gaita *et al.*, 2014; KEBS, 2014). Kenya has vehicle emission limits stipulated in the standard KS1515 (KEBS, 2014), but these are not implemented or enforced as the motor vehicle inspection unit (MVIU), the institution mandated to do so, lacks the capacity and resources (Cameron *et al.*, 2012).

Transport is one of the key sectors for GHG mitigation identified by the United Nations Framework Convention on Climate Change (UNFCCC) (United Nations, 1992). In 2015, Kenya submitted its first Intended Nationally Determined Contribution (INDC) with the aim of reducing GHGs emissions (Ministry of Environment and Natural Resources, 2015). This was informed by a top-down GHG inventory using fuel consumption as a measure of activity within the road transport sector. This inventory identified the transport sector as emitting 10% of Kenya's GHG emissions (Cameron *et al.*, 2012; Ministry of Environment and Natural Resources, 2015). However, this top-down assessment of mitigation options was only conducted for long-lived GHGs i.e. CO_2, CH_4 and N_2O. A bottom-up approach to assessing emissions of both air pollutants and GHGs in the road transport sector would therefore provide a more detailed basis to assess the likely effectiveness of different mitigation strategies. Furthermore, transport policy making is difficult if the emissions of the various measures are not properly quantified as planning relies on both a baseline assessment and an analysis of the likely benefits of appropriate mitigation measures (Ou *et al.*, 2010). Limited data availability was identified as a hurdle in identifying mitigation scenarios in the transport sector to meet Kenya's 2030 targets (Cameron *et al.*, 2012). Therefore, more analysis is necessary to build an accurate and robust "bottom up" transport emissions inventory to support appropriate emission reduction strategies in relation to other emission sources.

This paper presents the first 'bottom-up' Kenyan transport emission inventory for emissions of SO_2, NO_X, CO_2, CO, CH_4, NMVOC, PM_{10}, $PM_{2.5}$, BC, OC and NH_3. Air pollution and GHG emissions for the base year, 2010, were estimated for road transport as well as emissions from all other major source sectors in Kenya to set transport within the context of the overall national inventory for Kenya. Road transport emissions were projected to 2050 based on historic trends in vehicle numbers as a function of gross domestic product (GDP) per capita. Mitigation scenarios were then compared to the BAU. The mitigation scenarios considered implementation of i) improved vehicle emission and fuel economy standards ii) improved public transport system, and iii) fuel share shift to more renewable energy sources. The implications of these changes for Kenya's GHG, air pollution and SLCP-relevant emissions were estimated.

4.2 Methodology

To analyse the current and future trends in vehicle emissions from Kenya's road transport sector, a detailed (bottom-up) road transport inventory model was created in which important economic and demographic drivers and historical data were used to project future emissions up to 2050. Additionally, to show the relative importance of the road transport sector, a simple inventory (top-down) was also created for the other emission source sectors. The overall methodology is shown in Figure 4.1. The data used to construct this inventory are summarised in Table 4.1, and described in detail in supplementary information. The inventory was constructed using the Long-range Energy Alternatives Planning system (LEAP) software (Heaps, 2016).

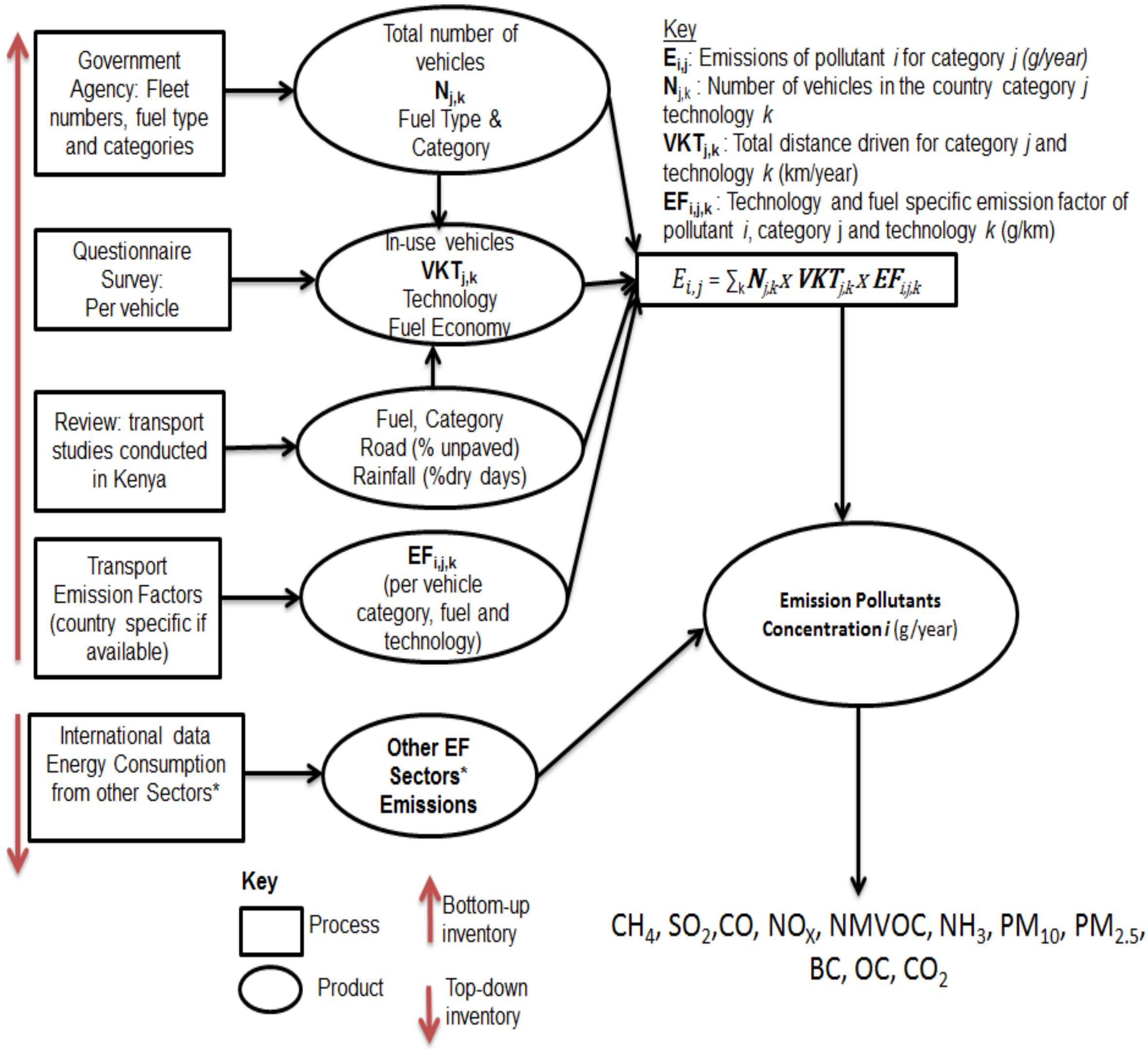

Figure 4-1: Methodology for estimating transport emissions.

The emissions for the non-transport energy sectors were quantified by using the IPCC methodology based in the top-down quantification of energy consumption (IPCC, 2006). The data for all non-transport fuel combustion sectors for Kenya were obtained from the International Energy Agency (IEA) for 2010 (IEA, 2012b) and emission factors were mainly derived from the EMEP/EEA guidebook (EMEP/EEA, 2013) and the IPCC (2006) guidelines. For non-energy sectors, such as agriculture and agricultural related activities, emissions were quantified using data from FAOSTAT on agricultural productivity (FAO, 2017). Further details of the quantification of the non-transport sectors are in the supplementary section.

Five scenarios were modelled based on previous studies that explore transport emissions mitigation in developing countries (Ou *et al.*, 2010; Aggarwal and Jain, 2014), in Africa (Shindell *et al.*, 2011; Lacey *et al.*, 2017) and in Kenya (Cameron *et al.*, 2012).

4.2.1 Transport Inventory for Kenya

To quantify emissions from the road transport sector in 2010, the number of vehicles of different categories, fuel use, and emission standards were compiled, along with distance travelled and emission factors for each type of vehicle, as shown in Table 4.1. There were 1.34 million vehicles in registered Kenya in 2010 (KNBS, 2013b), and, in the absence of data for vehicles in circulation (in-use vehicle), it was assumed the registered vehicles represent the number of in-use vehicles. The vehicle categories considered are passenger vehicles (private cars, taxis), light duty commercial vehicles (vans, pickups, and small trucks), heavy duty commercial vehicles (lorries and trucks), urban buses (*matatus* and bus coaches), motorcycles (*bodaboda*) and three-wheelers *(tuktuk*), and the proportion of vehicles in each category are shown in Table 4.2.

Table 4-1: Data for estimating emissions using a detailed vehicle emissions inventory. Numbers in the first column on the left of the table correspond to sections in this paper.

No.	**Inputs**	**Units**	**Description**	**Source of information**
S5.1	Number of vehicles in-use Category of vehicle Vehicle legislation and technology	-	(N): Total number of vehicles in-use Passenger (M1), light commercial (N1), urban bus (M2), heavy duty (N2, N3, M3), motorcycles (L3e) 3-wheelers (L2e) Conventional (pre-euro), Euro 1, Euro 2, Euro 3, Euro 4, Euro 5, Euro 6	(KNBS, 2013b, 2014b) (Mbandi *et al.*, submitted)
S5.2	Fuel use Fuel specifications	-	Type of fuel in use: petrol, diesel Fuel specifications: density and sulphur content	(KNBS, 2013b, 2014b; ERC, 2015b) (KEBS, 2007, 2010)
S5.3	Average distance travelled per vehicle	$\frac{km}{year}$	(M) :Average vehicle mileage also referred to as Vehicle Kilometres Travelled (VKT) per vehicle category	(Mbandi *et al.*, submitted)
S5.4	Average Fuel Economy (FE)	$\frac{g}{km}$	Average fuel consumption per vehicle category	(Mbandi *et al.*, submitted)
S5.5	Distance travelled on unpaved roads as a percentage of total	%	Average distance travelled on unpaved roads that would contribute to dust particles	(Ong'uti, 2015)
S5.6	Precipitation average per year	%	% of dry days considered to be < 0.25 mm precipitation per day	(BBC, 2015)
S5.7	Emission factors: NO_X, CO, NMVOC, Exhaust PM_{10} & $PM_{2.5}$, unpaved dust PM_{10}, &$PM_{2.5}$, CO_2, BC, OC, SO_2	$\frac{g}{km}$	(EF) Default emission factors are shown in Table S9 in supplementary	(Ntziachristos *et al.*, 2013; Kouridis *et al.*, 2014)

The proportion of vehicles using different types of fuel (diesel, petrol, hybrid) for Kenya (Table 4.2) was determined from ERC (2015) for light duty vehicles, and multiple previous studies for heavy duty vehicles (JICA, 2006, 2014; Ministry of Transport Kenya, 2011; Behrens *et al.*, 2017).

The emission reduction technology for new vehicles was determined by the prevailing emission standards in the year and country of manufacture, the quality of the available fuel, and other vehicle parameters (e.g. type of fuel, cylinder displacement). Imported vehicles manufactured in any particular year would normally comply with an existing standard, or a version of the standard of that year, from the relevant major world vehicle manufacturers in the EU, USA and Japan (Plotkin, 2016; Toubeau, 2016). However, the emission reduction capability of the technology for in-use vehicles can only be maintained if an effective I/M programme is enforced (Walsh, 2014). In Kenya, the absence of enforceable vehicle and fuel economy standards or an effective I/M program meant that the emission standard of all vehicles in Kenya were assumed to be equivalent to pre-Euro standards, even though the vehicles were manufactured to a higher standard initially.

Table 4-2: Number and type of fuel for each vehicle category. Data sources (Ministry of Transport Kenya, 2011; KNBS, 2013b, 2014b; ERC, 2015b).

Vehicle category	No. of vehicles	Diesel	Hybrid	Petrol
Passenger Vehicle	553,397	16%	0.01%	84%
Light Duty Commercial	226,876	12%	0.34%	87%
Heavy Duty Commercial	96,355	100%	0%	0%
Urban Buses (Matatu and Coach)	89,708	46%	0%	54%
Motorcycles (bodaboda)	371,747	0%	0%	100%
Three-wheelers (tuktuk)	2,152	68%	0%	32%

In the absence of recent national vehicle activity studies for Kenya as a whole for in-use vehicle fleet, we used data from a vehicle activity study conducted in the Nairobi Metropolitan region (NMR) (Mbandi *et al.*, submitted) (Figures S4 and S5). An assumption was made that the vehicle kilometres travelled (VKT) and fuel economy (FE) for NMR is equivalent to national VKT and FE.

The exhaust emissions (g/km) were calculated by multiplying activity data (VKT per year) by the emission factors as shown in equation 4.1:

$$E_{ij} = \sum\nolimits_{k} (N_{j,k} \times M_{j,k} \times EF_{i,j,k}) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots Equation\ 4.1$$

where,

$\mathrm{M_{j,k}}$ = total annual distance driven by all vehicles of category j and technology k (km/yr),

$EF_{i,j,k}$ = technology specific emission factor of pollutant i for vehicle category j and technology k (g/km),

$M_{j,k}$ = average annual distance driven by per vehicle category j and technology k (km/yr),

$N_{j,k}$ = number of vehicles in nation's fleet category j and technology k.

In the absence of national vehicle emission factors, default emission factors derived from the Tier 2 factors given in the European Monitoring and Evaluation Programme / European Economic Area (EMEP/EEA) emissions guidebook (Ntziachristos et al., 2013; Kouridis et al., 2014) for all vehicle categories except three-wheelers and motorcycles for which Indian emission factors were used (ARAI, 2008). The emission factors used for each vehicle, disaggregated by vehicle category, fuel type and technology are shown in Table S8.

To determine the emissions contributions to PM_{10} and $PM_{2.5}$ from re-suspended dust from unpaved roads, we determined the percentage of travel on unpaved roads and the percentage of dry days. Kenya, like most SSA countries, has a large number of unpaved roads estimated at 93% of all roads (Ong'uti, 2015; Fukubayashi *et al.*, 2016), while 15% in the NMR are unpaved (Gachanja, 2012). However, 67% of the vehicles in circulation are to be found in NMR (Gachanja, 2012), this resulted in an estimated 41% of national travel being on unpaved roads (supplementary, Table S6). Dry days were defined as those with equal or less than 0.1 mm precipitation per day, and the percentage of such days was calculated from historic meteorology data for Kenya per year (BBC, 2015) (Tables S6 and S7). Equation 4.2 was then used to calculate emission factors for PM_{10} which were converted to $PM_{2.5}$ factors assuming $PM_{2.5}$ is 10% of PM_{10} from unpaved road dust (Gillies *et al.*, 2005; EPA, 2006).

$$PM_{10}\left(Emission\ factor, \frac{g}{km}\right) = 3\ x\ W\ x\ S \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots.. Equation\ 4.2$$

S: Average speed in km/hr (assume 30 km/hr)

W: Average vehicle weight in tonnes (assumed to be 0.4 t for 2-wheelers, 1 t for 3-wheelers, 1.4 t for passenger cars, 2.5 t for light commercial vehicles and 5 t for heavy duty vehicles (trucks and buses)).

For the other transport sectors (rail, domestic shipping and domestic aviation), emissions were determined through a top-down inventory based on fuel consumption data (IEA, 2012b).

4.2.2 Assessment of uncertainties in the road transport emission inventory

Uncertainties have been estimated by combining individual uncertainties from emission factors, fuel characterization and activity data (Bond *et al.*, 2004). To estimate the uncertainty of road transport emission estimates for Kenya two sources of errors were considered; emission factors and input activity data. The activity data for Kenya together with the uncertainty information was available from a previous study (Mbandi *et al.*, submitted). Uncertainty for EMEP/EEA emission factors has been quoted to be between 50-200% as they are estimated from emission measurements of a small number of representative vehicles in European driving conditions (Ntziachristos *et al.*, 2013). In addition, systematic uncertainty may also result from the application of these European-derived emission factors to Kenya, as Kenya driving conditions are dissimilar to European driving conditions. Kenya's driving condition are characterised by heavy traffic congestion in urban areas, poorly maintained roads (Kinney *et al.*, 2011; Gachanja, 2012) which are mostly unpaved, and even those that are paved often have potholes. We account for the emission factor error by assuming 75% uncertainty, but we do not have enough data to account for the magnitude of systematic bias. However, we do assume a lower emission standard for the Kenyan fleet even when the newly registered vehicles are less than 8 years old.

In line with the recommendation for EMEP/EEA (2016) for uncertainty calculations we combined the random uncertainty of the emission factors and activity data using Equation 3 (Kouridis *et al.*, 2009, 2017; Ntziachristos *et al.*, 2013) .

$$U_{total} = \sqrt{U_1^2 + U_2^2 + U_n^2} \dots\dots\dots\dots\dots\dots\dots\dots\dots. Equation\ 4.3$$

where

$U_{1\text{-}3}$: are the percentage uncertainties (half the 95% confidence interval) associated with, vehicle kilometres travelled (VKT) (U_1), Fuel Economy (FE) (U_2) for Kenyan fleet and emission factors (U_3).

U_{total}: is the percentage uncertainty in the product of the quantities (half the 95% confidence interval divided by the total and expressed as a percentage).

4.2.3 Baseline construction of business as usual scenario

The baseline 'Business as usual' (BAU) scenario was used to project vehicle number from 2010 to 2050 based on the linear relationship between vehicle number, disaggregated by vehicle type and GDP per capita between 1998 and 2013 (Figure S11).

In the BAU scenario, vehicle emission standards, fuel economy standards and fuel share were kept constant between 2010 and 2050. This is because the BAU scenario accounts only for current transport sector policy, legislation, regulations, and standards that have been implemented and enforced in Kenya. Here a clear distinction is made for 'implementation', where a relevant plan or system is starting to be used and 'enforcement' where laws/regulations were applied and supported by the legislative arm of the country. For example, fuel quality improved in 2016 (KEBS, 2007, 2010; ERC, 2015b), this was implemented and enforced thus in the BAU scenario this fuel quality improvement is included (see the Figure 4.5), however vehicle emission and fuel economy standards were not enforced, thus in BAU they were kept constant to 2050. Vehicle mileage and fuel share is kept constant from 2010 for all vehicles.

4.2.4 Transport mitigation scenarios

The Kenyan government has made a commitment to reduce approximately 3.5 Mt CO_2 equivalents from the transport sector and 30% GHG from all sectors compared to a business as usual scenario (BAU) by 2030 (Cameron *et al.*, 2012; Government of Kenya, 2013; Ministry of Environment and Natural Resources, 2015). The transport mitigation actions previously identified were to improve vehicle fuel efficiency, fuel use shift to biofuels, improvement of public transport through implementing light rail transport (LRT) and bus rapid transit (BRT) and shift freight from road to rail (Cameron *et al.*, 2012; Government of Kenya, 2013) . Therefore, this study builds on the strategy (shown in Table 4.3) adopted by the government of Kenya and a proposed alternate policy to biofuel use; here we proposed to consider increased market penetration of compressed natural gas (CNG) use in urban buses and use of electric motorcycles. In addition, we assess the policy interventions of strict vehicle emissions standards targeting vehicle technology and fuel quality to further mitigate the emissions from transport sector.

Five mitigation scenarios were modelled to estimate changes in emissions from different changes to the transport fleet in Kenya. These scenarios are summarised in Table 4.3. Vehicle emission standards in Africa are based on restriction of vehicle age on importation (Lacey *et al.*, 2017), for Kenya that is 8 years (Cameron *et al.*, 2012; Gaita *et al.*, 2014; ERC, 2015b). The Motor Vehicle Inspection Unit (MVIU), under the National Transport and Safety Authority (NTSA) agency, in the Ministry of Transport, have the mandate to enforce Kenya's code of practice for inspection of road vehicles which includes vehicle emissions tests and limits (KEBS, 2014), although they have limited capacity and resources. Hence in mitigation Scenario 1 we assume that by 2050, Kenya has fully implemented better vehicle standards and fuel quality (Euro IV or equivalent) (Shindell *et al.*, 2011; Lacey *et al.*, 2017) and has an enforced I/M program (see Table 3). For the mitigation scenarios, improved fuel standards mean that sulphur content for diesel reduces from 500 ppm to 50 ppm from 2016 onwards. By 2050, Fuel Economy (FE) in all vehicles for Scenario 1, will equal Japanese FE Targets for 2015 (JAMA, 2016): Passenger (44 g/km), Light duty commercial (48.2 g/km), Heavy Duty commercial (122.3 g/km), Urban buses (124.6 g/km) and Indian in-use FE in 2015 (Goel *et al.*, 2015) (Three wheelers (26.9 g/km), Motorcycles (16.2 g/km). Future vehicle Emission standards for Scenario 1: Passenger: Euro IV, Light duty commercial: Euro IV, Heavy Duty: Euro 4, Urban buses: Euro 4, Three wheelers: 4 stroke Euro II, Motorcycles: 4 stroke Euro II.

Table 4-3: Scenario generation for emissions reduction from the road transport sector in Kenya

Kenya GHG scenario	Description of Kenya GHG scenario	This Scenario
Improve fuel economy (passenger vehicles)	Scrap old cars and restrict imports 7% fuel economy improvement by 2030	***Scenario 1: SC1_FEVES*** Improve vehicle emission standards and fuel economy standards to meet future emission Strategy (% of fleet to meet new standards) 2010 (0%), 2020 (5%), 2030 (50%), 2050 (100%)
Improve fuel economy (heavy duty vehicles)	Improved efficiency systems in the trucking sector, 2020 (3%), 2030 (10%)	
Fuel shift: Bio-ethanol	10% fuel shift to bio-ethanol from 2015 and onwards to 2030	**Scenario 2: SC2_CNG** Fuel shift share from Diesel to CNG Euro III by 2050 (Goel *et al.*, 2015) Strategy: public service vehicles (PSV) buses 2010 (0%), 2020(5%), 2030 (50%), 2050(100%) **Scenario 2: SC3_Electric** (Ou *et al.*, 2010) Strategy: (% of electric motorcycle fleet) 2010(0%), 2020 (1%), 2030 (2.5%), 2040 (5%), 2050 (10%)
Fuel shift: Bio-diesel	2% fuel shift to bio-diesel from 2015, 10% in 2020 and onwards to 2030	
Improve public transport by introducing LRT & BRT in NMR	5% of public transport demand to be met by BRT and LRT by 2030	**Scenario 4: SC4_BRT** (Cameron *et al.*, 2012) % of public transport to be met by BRT 2010 (0%), 2030 (5%), 2050 (10%) Assumptions 270 BRT buses, 29 km fully implemented in 2030 assumed to pull 100% (11 000) from 14-seat matatus in Nairobi Strategy Add 270 buses Euro III in 2030 with FE 124.6 g/km, remove 11 000 matatus

		Scenario 5: SC5_DIES Change light duty passenger vehicles to 55% diesel Euro IV by 2050

4.3 Results

4.3.1 Emissions for the base year (2010)

4.3.1.1 Estimate of emissions from all sectors for base year

The emission shares of 11 pollutants for 2010 by major source sector are shown in Figure 4.2. Transport (road and other forms of transport) dominated the emissions of NO_x and PM_{10}, was the major fraction of $PM_{2.5}$ emissions, and made smaller, but not insubstantial contributions to CO_2, NMVOC, CO, BC and OC emissions. The dominant contribution of transport emissions to PM_{10} reflects the larger emissions of road dust in the coarse fraction of particulate matter, while NO_x emissions from transport derive from tailpipe emissions. Hence road transport emissions make a substantial contribution to Kenya'a air pollutant and greenhouse gas emissions. However, the base year emission inventory emphasises that reducing road transport is just one of a number of source sectors that must be focussed on to comprehensively reduce air pollution and GHG emissions. Other source sectors which made substantial contributions to pollutant emissions in Kenya in 2010 include the residential sector, which contributed the major fraction of BC, OC and CO_2 emissions, cottage industries, which dominated NMVOC and CO emissions, and agriculture, from which the major fractions of NH_3 and CH_4 emissions originate.

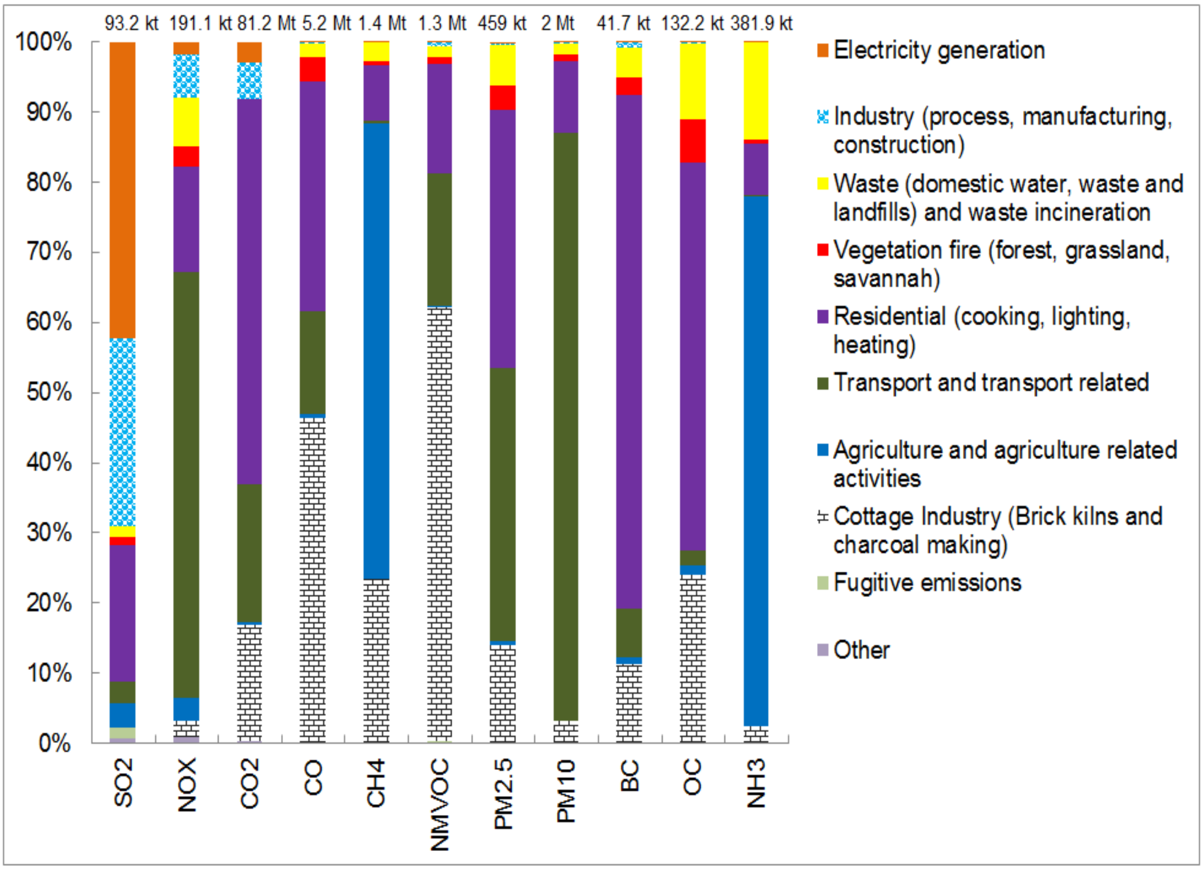

Figure 4-2: The 2010 fractional sectorial contribution by emitted species.

The contribution of Kenya's transport sector emissions from road transport, domestic shipping, railway and domestic aviation for 2010, are shown in Figure 4.3. International shipping and international flights were not accounted for in the national emissions inventories because they occur in international territories. Road transport dominates emissions of all pollutant across the transport sector (Figure 4.3). However, the contribution of different modes of road transport varies for the different pollutants. Heavy duty vehicles together with urban buses contribute an estimated 62% of NO_X and 49% of BC emissions. Motorcycles make the dominant contributions of NMVOC, OC, CO and $PM_{2.5}$, while passenger cars make the dominant contributions to NH_3, CH_4, and CO_2.

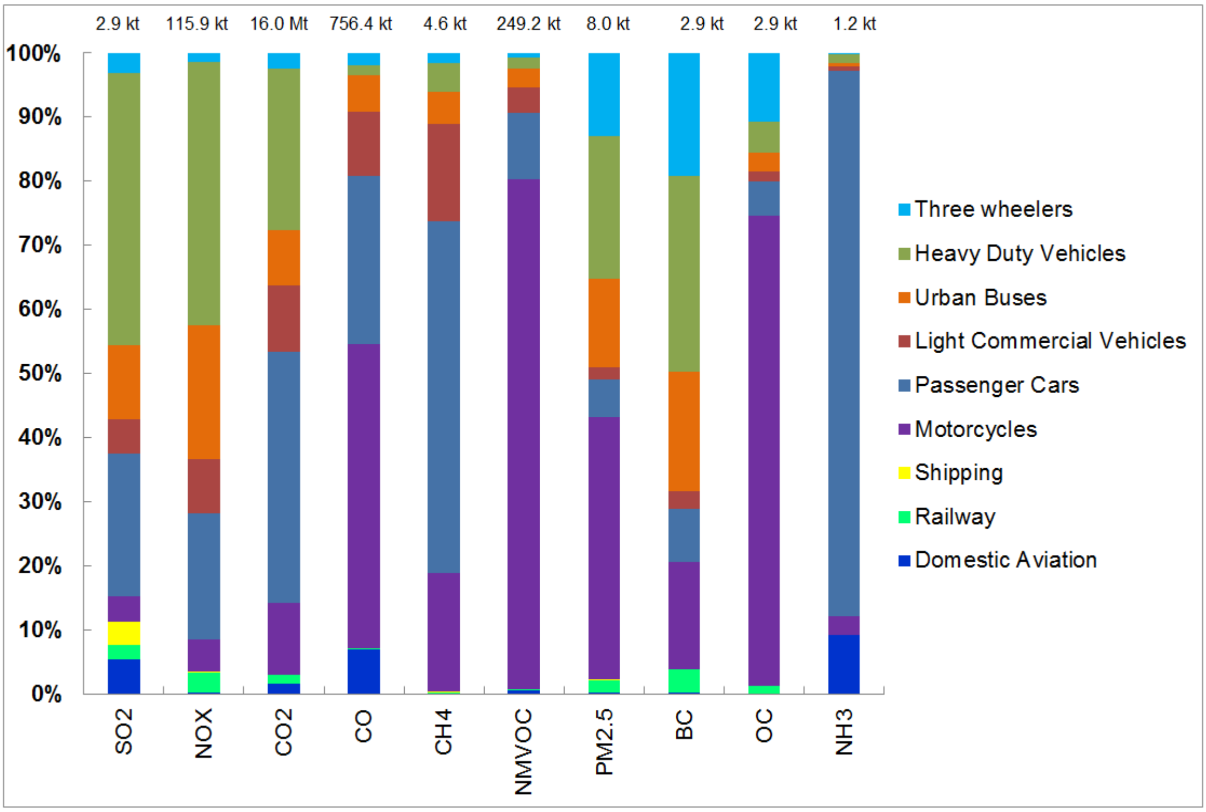

Figure 4-3: Base year emission concentrations proportion for transport sector in 2010

4.3.2 Future trends

Emission inventory projections were created for the BAU scenario. Different mitigation scenarios, described in Table 4.3, were also constructed and the results are discussed in the sections that follow.

4.3.2.1 BAU

The vehicle population growth projection for the BAU scenario is shown in Figure 4.4. In 2010, 1.4 million vehicles were registered in Kenya, 40% are passenger vehicles, 27% motorcycles, 16% light commercial, 7% heavy duty, 6% urban buses and 4% three wheeler. By 2030, the vehicle population is projected to increase to 5.7 million vehicles with motorycles becoming the largest proportion of the vehicle fleet (56%), followed by passenger vehicles (28%). In 2050, Kenya's total vehicle fleet is projected to be 21.6

million vehicles and the motorization rate increases to 226 vehicles per 1000 people, the largest proportion being motorcycles (63%).

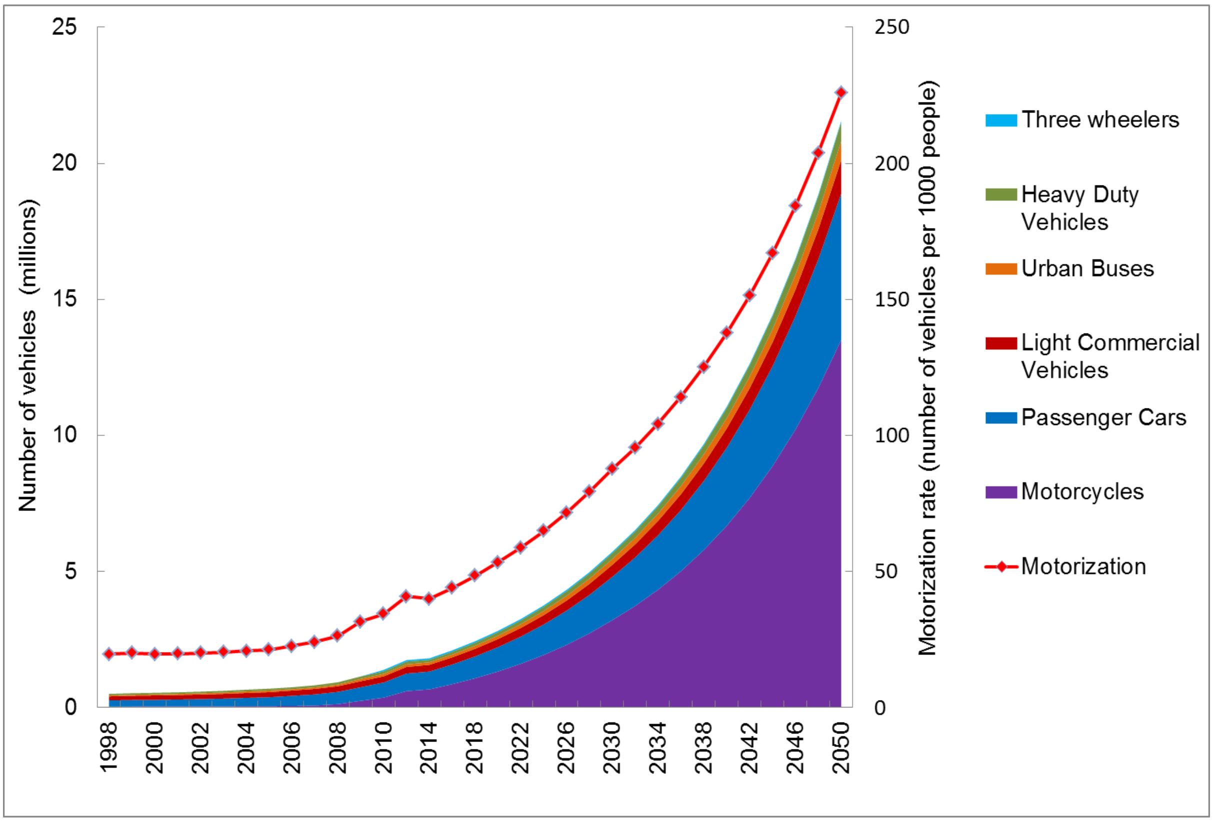

Figure 4-4: The historic trend (1998-2010) and future projection (2010 to 2050) of the total number of vehicles together with motorization rates (number of vehicles per 1000 people) Source data (KNBS, 2013b; World Bank, 2014).

The effect of these changes in the number of vehicles of each type on pollutant emissions is shown in Figure 4.5. Emissions for different species from Kenya road transport sector up to 2050, in the BAU, are projected to increase approximately 4-fold for SO_2, 9-fold for NO_X, 11-fold for CO_2, 23-fold for CO, 13-fold for CH_4, 31-fold for NMVOC, 19-fold for $PM_{2.5}$, 11-fold BC, 28-fold for OC and 10-fold for NH_3.

By 2050, motorcycles make the dominant contribution to all pollutants except for NO_X and NH_3, contributing 95% of OC and NMVOC, 83% of CO, 81% of $PM_{2.5}$, 56% of BC, 47% of CH_4, 42% of SO_2 and 36% of CO_2 (Figure 4.5 and Figure S12), driven by the disproportionate increase in the motorcycle fleet compared to other vehicles. Heavy duty vehicles make the dominant contributions to NO_X by 2050 (34%), followed by passenger cars (22%) and then motorcycles (21%), whilst passenger cars make the dominant contributions to NH_3 (87%).

4.3.2.2 Effect of mitigation scenarios on road transport emissions

The projections of Kenya's vehicle emissions for select pollutants in the mitigation scenarios from 2010 to 2050 are shown in Figure 4.5, and for all pollutants in Figures S7.11-S7.22.

The most effective scenario for reducing emissions for all pollutants was SC1_FEVES except in reduction of NH_3, for which the most effective scenario was SC5_DIES. SC5_DIES was the second most effective scenario in reducing total SO_2, NO_X, CO_2, CO, CH_4 but showed increases in total $PM_{2.5}$, BC and OC. The second most effective scenario after SC1_FEVES in reduction of NMVOC, OC and $PM_{2.5}$ was SC3_ELEC, and for BC was SC2_CNG. However, the SC2_CNG scenario showed an increase in total CH_4 emissions, whilst showing substantial emission reductions in NO_X emissions.

SO_2 in all the scenarios initially increased up to 2016, and then decreased to 2020 before increasing again to 2050. However, when compared to the BAU, the SC5_DIES scenario emissions of SO_2 are 4% higher in 2015 then decrease by 11% and 29% of BAU emissions by 2030 and 2050 respectively. Reductions of SO_2 emissions were somewhat larger in the SC1_FEVES scenario with decreases of 17% by 2030 and 62% by 2050 relative the BAU. Emission of SO_2 for the other three mitigation scenarios did not differ significantly from the BAU scenario. Emission reduction of CO_2 and CH_4 follow a similar trajectory, whereby SC1_FEVES show the biggest reductions in 2030, 17% for both CO_2 and CH_4, and in 2050, 61% for CO_2 and 63% for CH_4. Emissions from five species; BC, OC, NMVOC, $PM_{2.5}$ have 93%-98% reduction in the 2050 SC1_FEVES scenario.

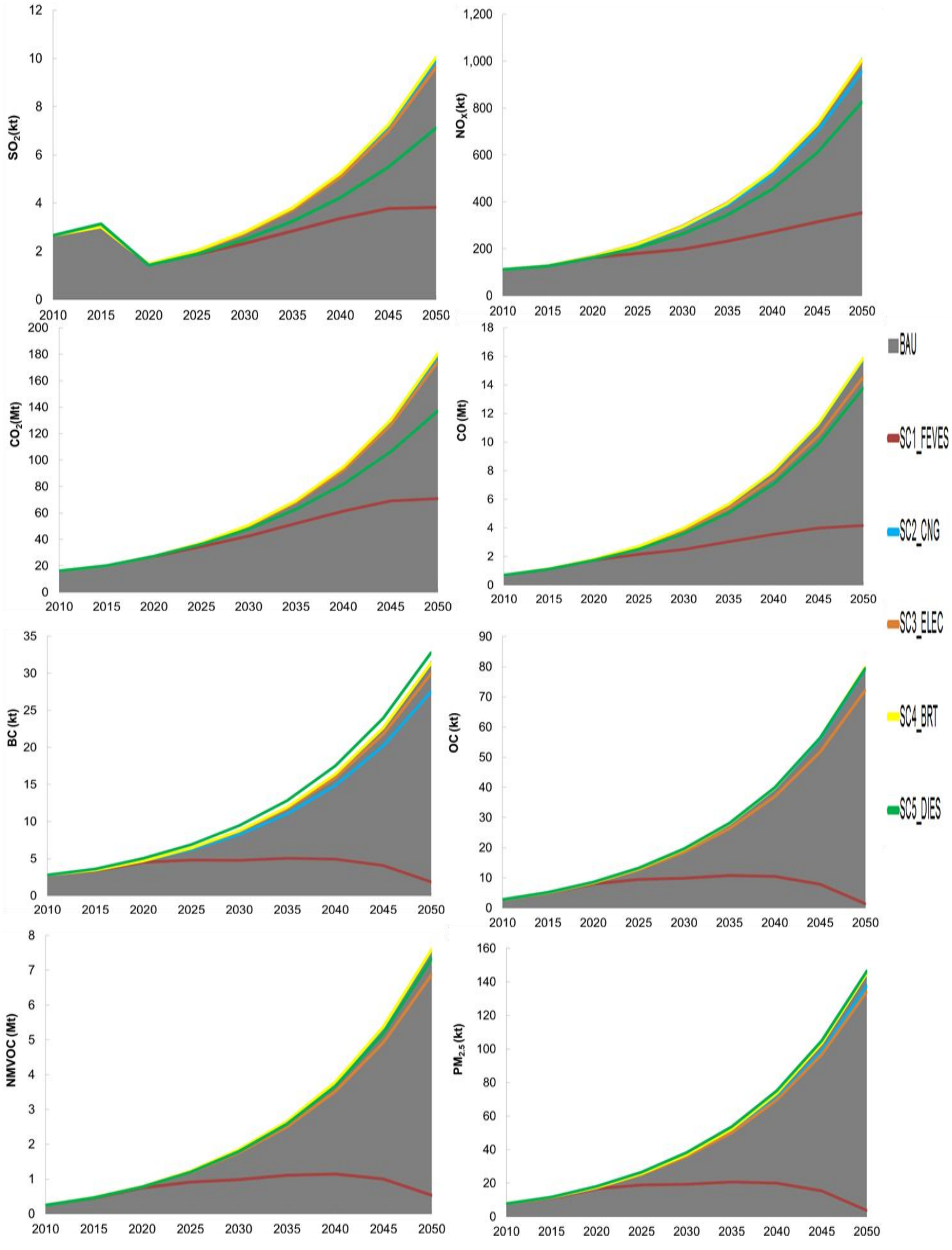

Figure 4-5: Total select emissions from Kenya's road transport sector in different scenarios, 2010-2050.

The reduction potential of the mitigation scenarios from BAU for different vehicle types for Kenya from 2010 to 2050, are presented in Figure 4.6. All scenarios were calculated for all pollutant species, the full set of results can be found in S7.23 - S7.34, Figure 4.6 presents results for selected pollutants.

For NO_X, all scenarios in general show a decreasing trend from 2010 to 2050 when compared to the BAU scenario (Figure 4.6, top left). In scenario SC1_FEVES, NO_X emissions from light commercial vehicles and passenger cars show the largest reductions (>90%) followed by urban buses (73%) and heavy duty vehicles (70%). The SC5_DIES scenario shows the second largest NO_x emission reductions in 2050 for both passenger cars (81%) and light commercial vehicles (23%) with the SC2_CNG scenario showing the second largest reduction (16%) for urban buses. SC5_Electric and SC4_BRT show modest reductions, less than 10% by 2050.

Carbon dioxide emissions from light commercial vehicles and passenger cars in scenario SC1_FEVES had the largest estimated reductions (>70%) compared to BAU in 2050, whilst motorcycles and three wheelers show over 55% reduction in 2050. The SC5_DIES scenario CO_2 emission reduction for passenger cars was almost as large as for the SC1_FEVES whilst light commercial vehicles showed a slight (1%) increase. For urban buses, the SC2_CNG scenario was the second most effective for CO_2 emission reduction, with a 30% reduction by 2050. SC3_Electric and SC4_BRT show modest CO_2 reductions (<10%) for motorcycles and urban buses respectively by 2050.

The SC1_FEVES scenario generally produced the highest reductions in NMVOC emissions, compared to BAU in 2050, for all vehicles types: 63% for three-wheelers and >93% for the remaining categories (Figure 4.6). However, the SC5_DIES scenario NMVOC emissions reductions for passenger cars (98% by 2050) were higher than in all other scenarios although for light commercial vehicles, the 2050 reduction (47%) was less than half that for SC1_FEVES. For urban buses, the SC2_CNG scenario shows the second largest NMVOC emission reduction by 2050 (32%) after SC1_FEVES and the

SC3_Electric scenario show the second highest reduction (~10%) for motorcycles by 2050.

The $PM_{2.5}$ emissions reductions, compared to BAU in 2050, are generally highest in SC1_FEVES at >90% for heavy duty vehicles, motorcycles and urban buses and >80% for all other vehicle categories (Figure 4.6, bottom right). However, for urban buses, the highest emission reduction (99% in 2050) was shown in the SC2_CNG scenario. For the SC5_DIES scenario, passenger cars and light commercial vehicles initially show a $PM_{2.5}$ emission increase of 50% and 77% respectively by 2020, but this reduces rapidly to 2050 by which time there is a reduction of over 50% compared with the BAU. The SC3_Electric and SC4_BRT scenarios show modest reductions in $PM_{2.5}$ emissions from motorcycles and urban buses respectively, both less than 15% by 2050.

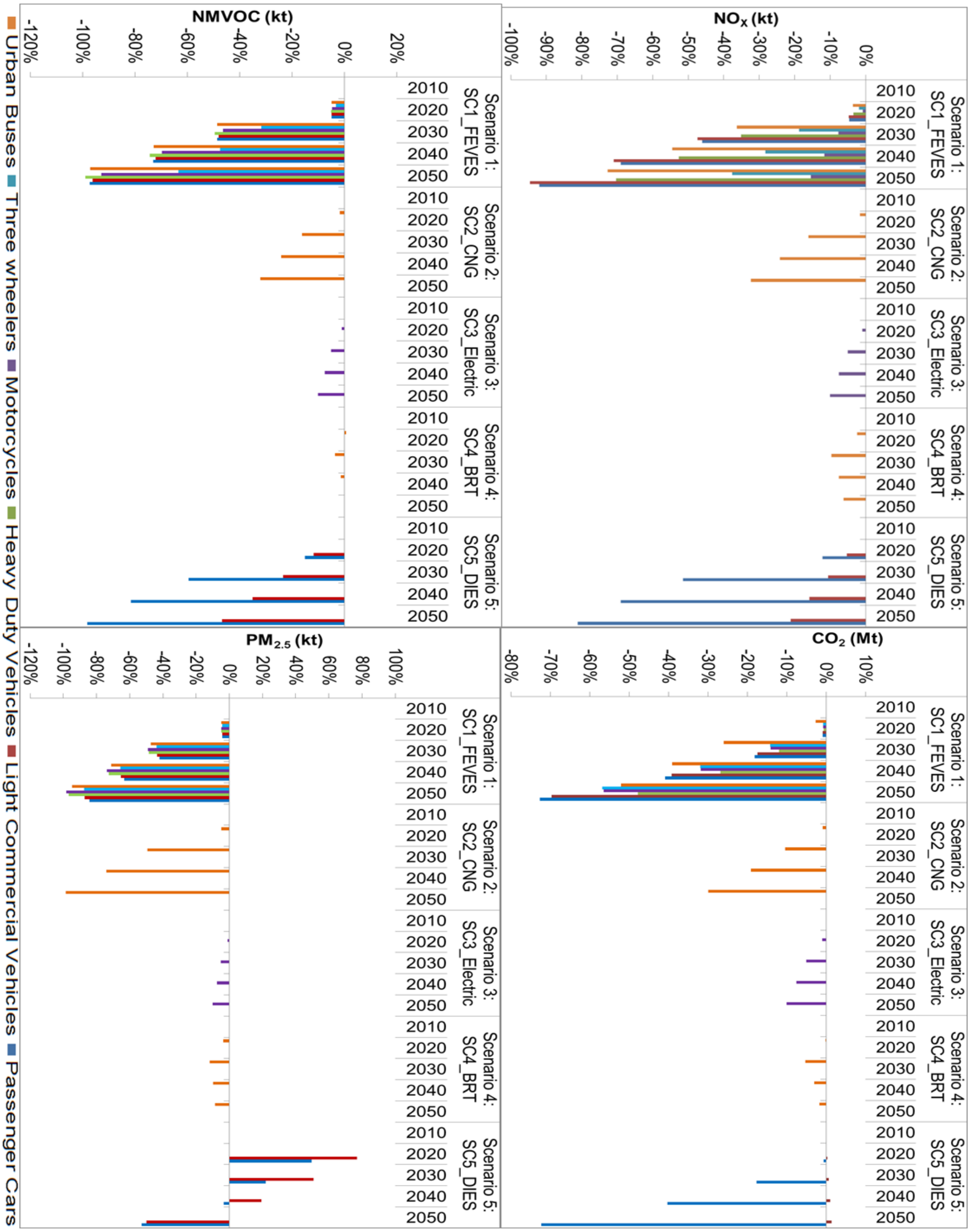

Figure 4-6: Select emission reduction in percentage from BAU of the different vehicle types in different scenarios 2010-2050.

4.4 Discussion

4.4.1 Transport policy implications for Kenya

Road transport in Kenya is characterised as being heavily congested along the main arterials, having inadequate transport infrastructure, poor safety, poor access, ill maintained and old vehicle fleet, poor fuel quality, absence of (or poor) regulations and lacking the resources to implement existing policy (Aligula *et al.*, 2005; Salon and Aligula, 2012). Increasing vehicle growth in the current situation will increase demand on fossil fuels in Kenya, increasing GHG and air pollutant vehicle emissions (Cameron et al., 2012; Government of Kenya, 2013). Kenya made a commitment to reduce approximately 3.5 Mt CO_2 equivalents from the transport sector and 30% GHG from all sectors compared to the business as usual scenario (BAU) by 2030 (Cameron *et al.*, 2012; Government of Kenya, 2013; Ministry of Environment and Natural Resources, 2015). The transport mitigation actions identified were to implement a mass transit system for Nairobi and surrounding areas, comprising light rail and bus rapid transit (BRT) (Cameron et al., 2012; Government of Kenya, 2013). However, lack of data on vehicle mileage/activity (VKT), type of fuel used per vehicle type, fuel economy for the different vehicle types were identified as key challenges in creating a GHG inventory and a reference case for projecting to 2030, as Kenya lacks a comprehensive detailed transport emissions inventory (Cameron et al., 2012). This study estimated that a substantial fraction of total national CO_2 emissions (20%) came from road transport in 2010, and these emissions were projected to increase substantially into the future. Hence, to achieve the stated goals of Kenya's INDC, controlling emissions from transport will be important. This study shows that the implementation of a BRT system may not be sufficient to achieve necessary GHG emission reductions, and that focussing on improving vehicle emissions standards, and fuel economy across the Kenyan vehicle fleet may be more effective in achieving this. Carbon dioxide is the main long-lived GHG that transport contributes to, and therefore other sectors should be focussed on reducing emissions of other GHGs, such as CH_4, which derive predominantly from agriculture.

In addition to climate impacts, increased motorization in Kenya has also led to increased congestion, road accidents and air pollution especially in urban areas (Aligula *et al.*, 2005; Odhiambo *et al.*, 2010; Kinney *et al.*, 2011; Cameron *et al.*, 2012; Gachanja, 2012; Shilenje *et al.*, 2016). An outdoor ambient air apportionment study conducted in Nairobi in 2009, found vehicle emissions contribute 39% of $PM_{2.5}$ (Gaita *et al.*, 2014). Prior studies have noted the absence of rigorous new action by government results in increasing air pollution emissions from transport. Road transport contributes a substantial fraction to emissions of those pollutants which degrade air quality, in particular to NO_x emissions (Shindell *et al.*, 2011; Klimont *et al.*, 2017; Susan C. Anenberg *et al.*, 2017). Emissions of NO_x contribute to the formation of ground-level ozone and secondary PM, both of which impact on human health, and ozone also damages crops leading to reduced crop yields, as well as harming natural vegetation. Hence reducing NO_x emission, in particular from road transport, could yield multiple benefits through reducing air pollution health, crop and climate impacts.

Kenya's government efforts to reduce road transport pollution through national regulation and standards align with their international commitments and Kenya's 'vision 2030' policy (Cameron et al., 2012; Government of Kenya, 2013). To curb vehicle emissions the government has used a vehicle and fuel standards approach: firstly, introducing a vehicle age limit for importation to 8 years and harmonizing fuel quality standards together with the other East African communities to achieve 50 ppm sulphur content for diesel and 150 ppm for petrol (ERC, 2015). Legislation for vehicle emission limits and inspection exists (KEBS, 2014), however government inspectorate lacks resources and capacity, therefore it is poorly implemented. Furthermore, without inspection and maintenance (I/M) programs in Kenya, newer fleet (less than 8 years) emissions also increase significantly (Pillot et al., 2014; Walsh, 2014). This study shows that the effective enforcement of vehicle and fuel economy standards on imported vehicles, to achieve the Euro IV standards to which the vehicles currently imported into Kenya are manufactured, would be the most effective action to reduce air pollutant and GHG emissions from the road transport sector. Implementation of the SC1_FEVES, SC2_CNG, SC4_BRT and SC5_DIES scenarios require strict vehicle emission standards up to Euro IV to be implemented and enforced by 2020 so that the fleet's standards start to improve gradually. These standards go hand in hand with better fuel standards and implementation of an I/M program for all vehicles in Kenya. Under the KS1515:2000 standard, commercial and public vehicles should undergo annual tests and private vehicles should have bi-annual tests if they are 5 years or older upon registration. These emission standards resemble the UK Ministry of Transport (MOT) vehicle tests and limits and are therefore are I/M tests. However at present, these tests are neither implemented nor enforced in Kenya. Furthermore, these tests have been found to be inadequate elsewhere as they have limited effectiveness (Ropkins *et al.*, 2009).

Fuel economy standards are often decoupled from vehicle emissions standards (Plotkin, 2016). However, Kenya has an opportunity to implement these standards concurrently given its improved fuel quality and vehicle imports from countries with Euro IV standards or higher. In Kenya, a recent study in NMR estimated in-use vehicle fleet economy characterised by vehicle category (Mbandi *et al.*, submitted). Assuming the Kenya's fleet fuel economy is similar to NMR for 2010, then for the SC1_FEVES scenario it was assumed Kenya's vehicle fleet will have an average annual improvement rate until the Kenyan fleet will reach the present Japanese fuel economy targets (JAMA, 2016) by 2050. SC1_FEVES required these improved FE standards to be implemented by 2020, so that the fleet FE gradually changes. However, the annual FE improvement estimated for this scenario (5-100%, by 2050) was higher than some previous studies: a 1% annual improvement of fuel economy for the South African fleet (Merven *et al.*, 2012), and 0.3-1.3% for Chinese fleet (Ou *et al.*, 2010). Both of these countries unlike Kenya have a large automotive manufacturing sector and have existing vehicle emission and fuel economy standards (Goyns, 2008; Ou *et al.*, 2010), whilst Kenya's projected improvement would be from non-existent standards, therefore this difference was deemed to be justifiable in the Kenyan context.

Prior studies have shown increasing the share of compressed natural gas (CNG) in buses and hybrid electric vehicles decreases vehicle emissions (Ou *et al.*, 2010; Merven *et al.*, 2012; Aggarwal and Jain, 2014; Goel and Guttikunda, 2015). China and India are global leaders in use of CNG, and in both countries, there are deliberate government efforts to build infrastructure to support CNG use through tax incentives and subsidies in addition to domestic availability of CNG (Wainberg *et al.*, 2017). In the current study's SC2_CNG scenario, a widespread adoption of CNG urban buses was envisaged by 2050, contributing to reductions of $PM_{2.5}$, CO_2, NMVOC, BC and NO_X (see Figure 5 & 6). The reductions of $PM_{2.5}$ in SC2_CNG is similar to India's significant reduction on initial introduction of CNG for buses and three-wheelers in the past decade (Goel and Guttikunda, 2015). Kenya, however does not have a domestic supply of CNG, but neighbouring Tanzania has abundant CNG reserves and is utilizing it for transport, targeting nearly 500,000 conversions by 2040 (United Republic of Tanzania, 2016). Therefore, Kenya could import CNG from Tanzania and CNG-fuelled buses from China or India, countries that are already Kenya's trading partners. Furthermore, government commitment would also be needed to build required infrastructure for CNG use such as filling stations (United Republic of Tanzania, 2016; Wainberg *et al.*, 2017). The Kenyan government now has a tax exemption for hybrid electric vehicle imports (Cameron *et al.*, 2012), therefore it is likely the percentage (~0.34%) of hybrid vehicles (see Table 2), will grow by 2050. However, in this study, we did not explore the hybrid vehicle scenario because emission factors for hybrid vehicles are scarce.

BRT has been successfully implemented in over 200 cities worldwide (Venter *et al.*, 2017) as it has advantages in increasing access to safe, convenient and affordable public transport (Matata *et al.*, 2017) while reducing intensive use of private cars thus decreasing vehicle emissions. In SSA, BRT has been implemented in Nigeria (Kolawole, 2010), South Africa (Merven *et al.*, 2012; Allen, 2013) and recently in Tanzania (Matata *et al.*, 2017). BRT systems are often complementary to existing informal transport systems in Africa (Venter *et al.*, 2017). Kenya is in the process of implementing BRT systems in Nairobi (Cameron *et al.*, 2012), although there have been delays. The current study, explored the implementation of the proposed BRT for Kenya in the SC4_BRT scenario. We assumed 11,000 (14 seater *matatu*) would be scrapped (ICCT, 2012). This was feasible based on the data from a BRT system in Tanzania that carries 120,000 passengers using a 21 km road with 177 buses (Mchomvu, 2016). The results showed emission reduction for $PM_{2.5}$ and BC and modest reductions for other emissions compared to SC1_FEVES (see Figure 5 and 6). Greater emission reductions could be achieved for Kenya from BRT by increasing the scope of the proposed project whereby Kenya would start to see benefits in reducing vehicle ownership, decreasing vehicle mileage which in turn reduces vehicle emissions and provides sustainable transport.

4.4.2 Comparison of emissions with previous estimates

In 2010, in Kenya, the transport sector in Kenya alone accounted for more than 61% of total NO_X, 20% of total CO_2, 19% of total NMVOC, 39% of total $PM_{2.5}$ and 84% of total PM_{10}. This indicates that transport should be a key sector for mitigation actions to reduce both air pollutant and GHG emissions. Transport does not account for a big proportion of BC (7%) and OC (2%), when compared to the residential sector and cottage industry that together contributes nearly 80% of BC or OC. The substantial contribution to OC and BC from the residential sector is due to use of fuel wood, charcoal and paraffin (kerosene) for fuel for lighting, cooking and heating, (Marais and Wiedinmyer, 2016). Charcoal production in Kenya accounted for the high BC and OC from the cottage industry sector. However, we need to account for BC and OC from the transport sector because, as certain vehicle types such as motorcycles increase (Figure 4.4), OC and BC emissions will increase nearly 11-fold and nearly 30-fold by 2050 respectively under the BAU scenario. Thus, motorcycles will account for 56% of BC emissions from road transport in 2050 and 95% for OC in this scenario. Post 2050, the number of vehicles may increase even further because, compared to other countries (Wu *et al.*, 2014), Kenya has not reached saturation in vehicle ownership. Therefore, impacts of these emissions to climate from transport sector are set to grow (see Figure 4.7 and 4.8).

The emission dataset developed for this study was compared to a global inventory compiled using ECLIPSE (Evaluating the Climate and Air Quality Impacts of Short-Lived Pollutants) dataset (IIASA, 2016) created using GAINS (Greenhouse-Air Pollution Interaction and Synergies) model (Stohl *et al.*, 2015), for Kenya (See Figure 4.2 and Figure S11). The residential sector in ECLIPSE accounts for the majority of emissions for almost all pollutants except CH_4 and NH_3, then major emissions from these two species are from the agriculture sector, for SO_2, major emissions are from Industry. This study's total emissions for Kenya, for all sectors for each species are higher than ECLIPSE emissions, except for BC (27% lower). The difference between these previous estimates and our work for total SO_2 and NO_X was over 40%, $PM_{2.5}$ and CO over 30%, CH_4 and OC over 20%, NH_3 over 10%, NMVOC difference was 58%, and the highest was PM_{10} with 83%. Differences in emissions in the transport sector accounted for the differences in emissions estimates between the two inventories. In this study, PM_{10} and $PM_{2.5}$ emission included re-suspended dust from unpaved roads in addition to tail-pipe emissions, and it was estimated that road dust accounts for 96% of $PM_{2.5}$ and 100% of PM_{10} emissions across the transport sector in 2010. This is due to the high fraction of unpaved roads in Kenya (Gachanja, 2012; Ong'uti, 2015; Fukubayashi *et al.*, 2016). ECLIPSE datasets do not estimate unpaved road dust (Klimont *et al.*, 2017), or other sectors such as savannah and grassland burning, which may account for lower emissions of OC, CO, PM_{10} and $PM_{2.5}$ in the ECLIPSE inventory.

In 2010, road transport was by far the major emissions contributor in the transport sector, as shown in Figure 4.3. This is consistent with previous studies where road transport in Kenya (when compared to rail and water) was identified as contributing 99% of transport GHG emissions in Kenya (Cameron et al., 2012). In an inventory for Africa, over 90% of CO and NO_X emissions from total transport was from road transport (Marais and Wiedinmyer, 2016). We did not include other forms of transport in the mitigation scenarios because we had limited data especially on rail transport which is set to grow in Kenya. However, emissions from other forms of transport may also increase in importance into the future. Rail emissions are set to increase because, as part of Kenya's vision 2030, there is planned expansion of current rail infrastructure to include light rail transport in the NMR and expand passenger and freight transport country wide (Cameron *et al.*, 2012). This could potentially reduce the demand for heavy duty vehicles to transport freight across Kenya, but this element of the future transport landscape in Kenya has not been evaluated in this study.

In a previous inventory for Africa, the transport sector was shown to emit 27% of total CO and 25% of NO_X (Marais and Wiedinmyer, 2016). In a follow up study of Africa's emissions contribution to OC from residential, industry, energy and transport sector, estimated that 7.5 kt were from transport sector representing 13% of total OC emissions in Kenya (Lacey *et al.*, 2017). The OC emissions from the transport sector in that study were thus an increase compared to a previous global study that had estimated OC from the transport sector in East Africa to be 4 kt in 1996, less than 1% of the total which included residential, industry and biomass burning (Streets *et al.*, 2004). In this study and ECLIPSE estimation, OC emissions were both ~2%, although NO_X emissions were 44% from transport for ECLIPSE, lower than this study's estimation, 61%. Therefore Lacey et al (2017) estimation of OC from transport was greater than this study's estimate whist ECLIPSE estimate for NO_X emissions from transport was less than this study's estimate.

The ECLIPSE data set, using the GAINS model, made three assumptions for high emitting vehicles which would be disparate for the Kenyan vehicle fleets, the first is the assumption that high emitters comprise of 20% of the fleet, in Kenya even though few tests emissions have been conducted, a previous study found 70% of vehicles failing emission standards for Kenya (Cameron *et al.*, 2012). The second assumption is that durability of emission controls has increased, this would not be the case for fleets that do not have the emission control as they are often removed or tampered with, furthermore in the absence of I/M as is the case in Kenya, these controls will malfunction (Pillot *et al.*, 2014). We do not have enough data to ascertain what fraction of emission controls are removed or tampered with in Kenya, IM240 dynamometer test for an I/M program in the USA found 35% of the fleet tested to have tampered with emission controls (Bishop *et al.*, 1996). The third assumption is amplification of emissions for high emitting vehicles (presumably with malfunctioning technology) to be a factor of 3-10 for all vehicle technologies, real-world emissions testing has proven vehicles with up to Euro V tested on the road instead of a laboratory have sometimes up to 300% higher emissions (Weiss *et al.*, 2012; Thompson *et al.*, 2014; Degraeuwe and Weiss, 2016).The fleets in developed countries are newer with the best technology, the Kenyan fleets in contrast are older and imported second-hand with poor I/M, thus the emissions differences will be higher and even greater discrepancy between real-world and laboratory testing. The DICE-Africa model from which Lacey et al (2017) based their estimation for Kenya's transport inventory assumed a ratio of motorcycles to cars to be 2.6 i.e. 49 motorcycles per 1000 people from an earlier study (Marais and Wiedinmyer, 2016). This estimate is greater than the number of motorcycles registered in Kenya in 2013, 18 motorcycles per 1000 people (KNBS, 2013b). This discrepancy may account for the higher OC emissions for Kenya in the transport sector from Lacey et al. (2017) compared to the present study. Kenya's GHG inventory estimates 10% CO_2 equivalent to be from the transport sector (Cameron *et al.*, 2012) compared with this study's estimate for CO_2 of 20% from the transport sector. In Cameron et al. (2012), a top-down inventory was used to estimate GHGs from the transport sector, but this method lacked end-user fuel split for the vehicles and activity data, they made an assumption on activity and fuel share which may have introduced a significant error in the estimate.

In 2010, motorcycles had the largest contribution of NMVOC, OC, $PM_{2.5}$ and CO emissions; passenger cars have the largest contribution of CH_4, NH_3 and CO_2 emissions; and heavy duty vehicles have the largest contribution of BC, NO_X and SO_2. The findings for motorcycles can be compared to a study conducted in West Africa, which looked at BC and OC emitted from motorcycles in 15 countries in 2002 (Assamoi and Liousse, 2010), where motorcycles' contribution of OC and BC were significantly higher compared to four-wheel vehicles (Assamoi and Liousse, 2010). However, Kenyan motorcycles are predominantly 4-stroke (Mbandi *et al.*, submitted), and not mainly 2-stroke (more polluting) as in West Africa. Looking at the ratio of motorcycles to four wheel vehicles assumed to be a 40-60% ratio (Assamoi and Liousse, 2010), this is also comparable to vehicle statistics of Kenya for 2013 (KNBS, 2013b). The proportion of the motorcycles, 39%, of the registered vehicles in 2013 surpassed the share of private cars, 37% (KNBS, 2013b). The increase in motorcycle numbers (mainly imported from Asia) in Kenya was spurred on by a tax waiver in 2011, but this incentive was scrapped in 2015 and an excise duty was introduced (KRA, 2016).

In comparison to available previous studies, the projected increase in emissions was higher for some pollutants. For example the BC emissions from road transport increases by a factor of 3 and OC by a factor of 7 to 2030 in the BAU scenario. This increase is higher than the 4-old, and 3-fold increase in BC and OC emissions across Africa projected by Liousse et al. 2014, where a similar BAU scenario was constructed i.e. present emission values are static in the absence of emission regulations.

The SC5_Electric scenario assumed a small percentage (10%) fleet of electric motorcycles in Kenya, but because by 2050 in the BAU, motorcycles will be 13.5 million representing 63% of the Kenyan vehicle fleet, this scenario showed significant emission reductions for SO_2, NO_X, CO_2, CH_4, CO and NH_3. For motorcycles, in the BAU we assumed uncontrolled (pre Euro) and then in SC1_FEVES we assumed Euro III and used Indian emission factors (Bharat III) instead of European emission factors. This is because the motorcycles in Kenya are imported from India and China; the engine is smaller compared to European, 150 cc and four-stroke engine, mostly used for public transport similar to India. By 2050, the results show that the motorcycles are responsible for the bulk of vehicle exhaust emissions for all species except NO_X, then heavy duty vehicles and NH_3, passenger cars are responsible. This is comparable to results from a previous study in Ho Chi Minh City, Vietnam where motorcycles comprised 87% of the vehicle fleet, responsible for the majority of vehicle emissions contributing 94% of CO, 68% of NMVOC, 61% (Ho and Clappier, 2011). China is the largest manufacturer of electric motorcycles (Fu, 2013) and they have opened various motorcycle plants in Africa, thus this offers a viable scenario whereby Kenya could reduce emissions from motorcycles.

In previous studies, the key source of PM emissions in the transport sector has been light and heavy duty trucks with diesel engines (Klimont *et al.*, 2017), especially in Europe where there is a large share of diesel fleets (Cames and Helmers, 2013; Toubeau, 2016; Klimont *et al.*, 2017). However, for Kenya in 2010, we found motorcycles were a key source of PM, followed by heavy duty and then urban buses (Figure 4.3). Heavy duty vehicles make the largest contribution to emissions of BC, NO_X and SO_2, these emissions' most effective reductions occur in scenario SC1_FEVES as shown in Figure 4.6. In Kenya, heavy duty vehicles and urban buses were considered to be uncontrolled using basic injection technology (UC Riverside, 2002). Kenya's fuel quality sulphur content in diesel (500 parts per million) improved ten-fold from 2010 to 2015, (specifications are shown in the supplementary section, Table S3) (KEBS, 2007, 2010), therefore there is a SO_2 reduction over this historical period in all scenarios. Diesel vehicles are responsible for the majority of the NO_X emissions which are key secondary $PM_{2.5}$ and O_3 precursors (Susan C. Anenberg *et al.*, 2017), therefore heavy duty vehicles with 100% diesel in Kenya, have the highest contribution of NO_X. Urban buses (matatus) in Kenya in 2010, comprised 46% diesel, a lower than expected proportion as there is a high importation of petrol-driven smaller vans, pickups and station wagon (ERC, 2015b) converted to matatus (Ommeh *et al.*, 2015; Behrens *et al.*, 2017), mostly circulating in rural areas. Even with this relatively low diesel proportion, urban buses are the second highest contributors of NO_X, BC and SO_2 after heavy duty vehicles. In addition to the scenario SC1_FEVES for maximum emission reduction, SC2_CNG shows significant reductions for BC and SC4_BRT has modest reductions for urban buses.

The rise of the European diesel light passenger vehicles appears to be waning (Schipper and Fulton, 2009; Cames and Helmers, 2013; Helmers, 2016), as some European cities have recently announced diesel vehicle bans by 2040 (Tietge and Diaz, 2017). Therefore, SC5_DIES scenario demonstrates the possibility of increasing diesel fleets as these second-hand vehicles are likely to become available for a market such as Kenya. This scenario, as shown in Figure 4.6, had an initial increase in 2020 for $PM_{2.5}$ emissions from light commercial vehicles and passenger cars compared to the BAU even though there was a gradual improvement in emission standards from 'uncontrolled' for passenger cars and 'conventional' for light commercial vehicles to Euro IV standard. This was due to changing the fuel share gradually for both types of vehicles, to have a higher diesel share for light duty vehicles similar to European share. This initial increase then gradually decreases to 2050 as the Kenyan fleet improves the share of Euro IV fleet.

4.4.3 Uncertainties and limitations

We considered uncertainties in vehicle usage, that is vehicle kilometres travelled (VKT), fuel economy (FE) and emission factors per vehicle category and per emission species, and Table 4.4 represents the combined uncertainties. In the projection we assume the percentage uncertainties in the base year emissions estimates will propagate over subsequent years, therefore uncertainties will tend to be correlated over time (Abel *et al.*, 2001).

Emission factors that over or under estimate emissions in the base year will probably do so in the subsequent years, therefore uncertainties due to emission factors will tend to be correlated over time.

Table 4-4: Table of individual uncertainties for vehicle mileage (VKT) fuel economy (FE) emission factors (EF) and the resultant combined uncertainties around pollutant emissions estimates.

	VKT (km/year) Kenya 2015	VKT CI %	FE (g/km) Kenya 2015	FE CI %	Combined uncertainty* (NO_X, CO, NMVOC, $PM_{2.5}$, BC, OC)	Combined uncertainty** (SO_2, CO_2, CH_4, NH_3)
Passenger Vehicle	22454.8	12%	161.1	12%	71%	71%
Light Duty Commercial	14764.3	13%	159.2	25%	71%	74%
Heavy Duty Commercial	38284.9	42%	234.6	50%	82%	86%
Urban buses	55315.8	7%	259.7	8%	70%	70%
Three Wheeler	41715.9	40%	62.5	54%	81%	88%
Motorcycle	29083.2	5%	37.3	8%	70%	70%

*70% Emission Factor uncertainty assumed, from a lower and upper bound estimate in uncertainty assessment of EMEP/EEA Tier 1 methodology (Ntziachristos *et al.*, 2013; Kouridis *et al.*, 2017). *Calculated from square root of % uncertainty VKT^2 and % uncertainty EF^2. **Calculated from square root of % uncertainty FE^2 and % uncertainty VKT^2.

There was uncertainty from predicting vehicle ownership increase because as income per capita increases the number of vehicles per 1000 people (motorization) increases, until a saturation point is reached (Dargay and Gately, 1999; Dargay *et al.*, 2007; Sillaparcharn, 2007; Merven *et al.*, 2012; Wu *et al.*, 2014). The Gompertz function (Dargay and Gately, 1999; Dargay *et al.*, 2007) has been used to model this relation and accounts for saturation levels, and parameters which determine the model curvature calculated from historic data. However this equation and parameters have been derived for developed countries with high income ($19,000-$46,0000) GDP per capita, and countries with middle income ($4,000-$9,6000) per GDP capita, and their motorization rates are well above Kenya's 44 vehicles per 1000 people and GDP per capita $1,400. Therefore, we considered that Kenya is far from reaching saturations levels; and assumed a linear relationship between the GDP per capita and the number of vehicles based on historical data for Kenya. Thus the BAU scenario for the road transport sector was created using available data (KNBS, 2013b, 2014b; World Bank, 2014) for two variables: GDP per capita and the number of vehicles in the individual vehicle categories from 1998-2013. These predictive relations are presented in supplementary section, S7.9. We also did not consider the rate at which a vehicle is scrapped (Merven *et al.*, 2012), as a function of the vehicle age being the probability of the vehicle remaining operational. With limited data for Kenya, we could not determine the parameters needed to either calculate the scrappage rate or determine the decay of mileage both of which would affect road transport emissions estimation for the fleet.

Dry days were defined as those with less than or equal to 0.1 mm rainfall per day, this is lower threshold than that assumed in Gillies et al. (2005), 0.25mm. Hence, the PM estimates from road dust in the present study are conservative, most likely an under-estimate. However, in the estimate of the proportion travelled on paved or unpaved roads, it was assumed that the VKT travelled on the paved/unpaved roads was a function of the road length. This is likely an over-estimate, as more vehicles will travel on the bigger paved roads. Thus in our estimation, these two factors would tend to balance out the uncertainty associated with the estimation of PM from road dust.

The activity data for vehicle VKT and FE was based on a previous study conducted in NMR which was assumed in this study to be representative of the whole country. This assumption may be reasonable for two reasons, one which may result in an over-estimate and the other an under-estimate. The first, since it is estimated 67% of all vehicles in Kenya circulate in NMR (Gachanja, 2012), two thirds of the activity data for NMR is representative for the country, the second, whilst the vehicles outside of Nairobi may circulate for longer distances (higher VKT), for example intra-country buses and trucks, these vehicles have better FE per km. However, further work needs to be done to establish the activity for vehicles outside of NMR as previous studies have shown circulation of vehicles in urban areas is often not the same as rural areas (Kholod *et al.*, 2016).

4.5 Conclusion

A detailed model has been developed to estimate the current and projected future trends of air pollutant and GHG emissions from Kenya's road transport sector between 2010 and 2050. An inventory was compiled of all major source sectors so that transport emissions could be set within the context of total national emissions. Five scenarios (SC1_FEVES, SC2_CNG, SC3_ELEC, SC4_BRT and SC5_5) were designed to project road transport emissions into the future, and the climate benefits of the implementation of these scenarios were assessed. The BAU scenario was used as a baseline reference scenario in which government is assumed to do nothing additional to influence the long term trends of road transport in Kenya.

It was found that in 2010, the transport sector emitted 15.95 Mt of CO_2, 115 kt of NO_X and 249 kt of NMVOC with road transport contributing nearly 97% of these emissions. Emissions for different species from Kenya's road transport sector up to 2050, in the BAU, were projected to increase 9-fold for NO_X, 11-fold for CO_2, 31-fold for NMVOC, 19-fold for PM, 11-fold for BC, 28-fold for OC. It was found that the mitigation scenario combining better fuel economy with improved emissions standards (SC1_FEVES) was the most effective reduction scenario for all species apart from NH_3 for which the most effective reduction scenario was the increased diesel usage (Euro IV standard) in light duty passenger vehicles (SC5_DIES). All mitigation scenarios generally showed reductions for all vehicle types for all emitted species apart from CH_4 in SC2_CNG (because of use of CNG-fuelled urban buses) and NH_3 in SC1_FEVES (because of NH_3 emitted from vehicles equipped with urea-based catalytic converters).

These results suggest comprehensive implementation of improvements in both fuel economy and vehicle standards in Kenya will have the most benefits for improving air quality and reducing Kenya's contribution to short and long-term climate warming, although a fuel shift to CNG or electric-powered vehicles, as well as investment in public transport, would also provide substantial benefits.

4.6 Supplementary

4.6.1 Section A: Data inputs for the inventory

Section details the input and sources of data needed for a detailed road transport inventory and a simple inventory for non-transport sector

S7.1 Number of vehicles in-use disaggregated by vehicle category

The historical data set of the cumulative number of vehicles registered from 1998-2013 in Kenya is shown in Figure S1, disaggregated into vehicle categories.

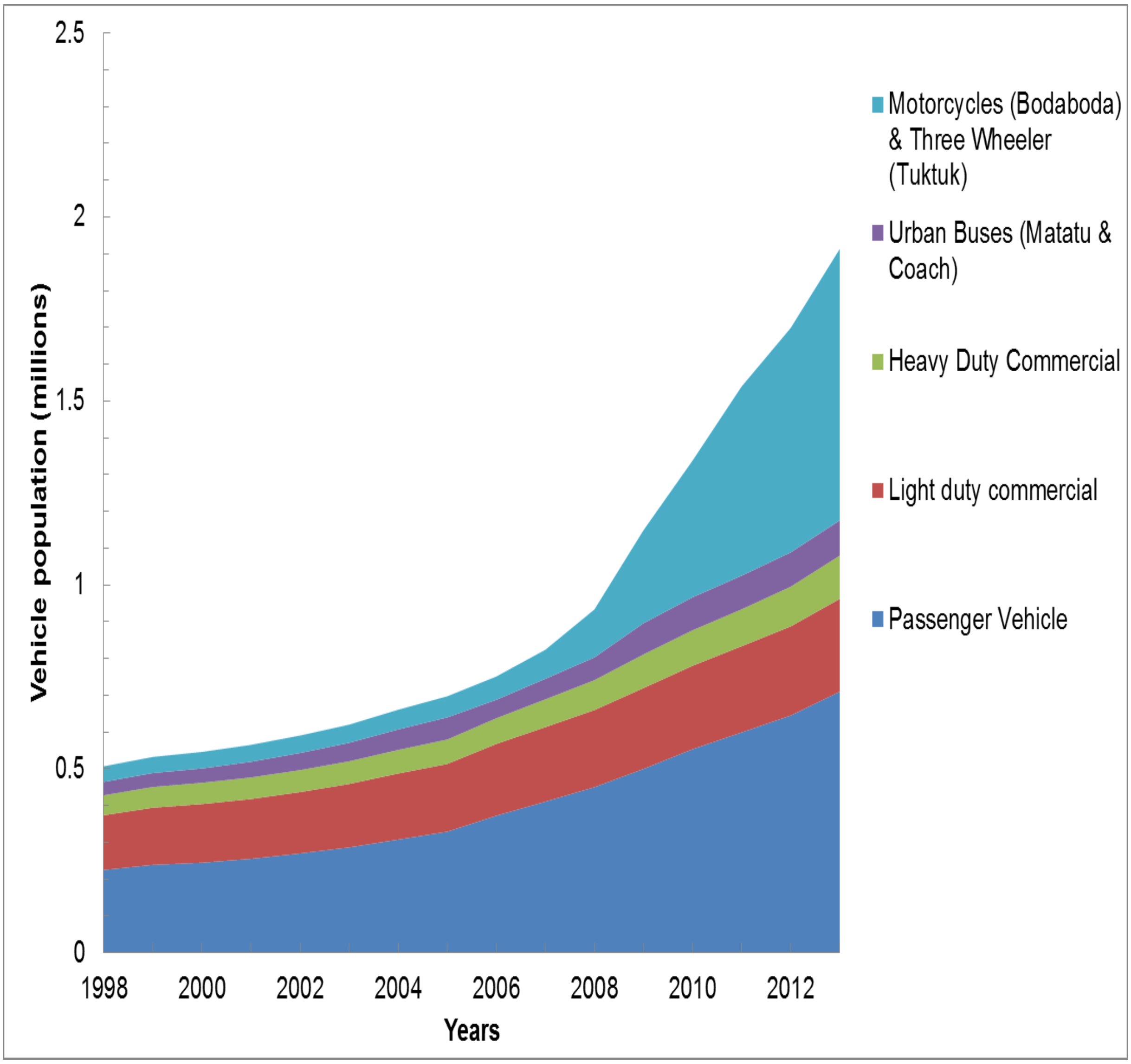

Figure S1: Historical data from 1998-2013 for the registered number of vehicles in Kenya excluding trailers. Source data: (KNBS, 2013b, 2014a).

S7.2 Vehicles in-use disaggregated by type of fuel used

The fuel use for the different vehicle categories for 2010 is shown in Figure S2. The categories in Kenya National Bureau of Statistics (KNBS) are adjusted in accordance with the classification shown in Table 1.

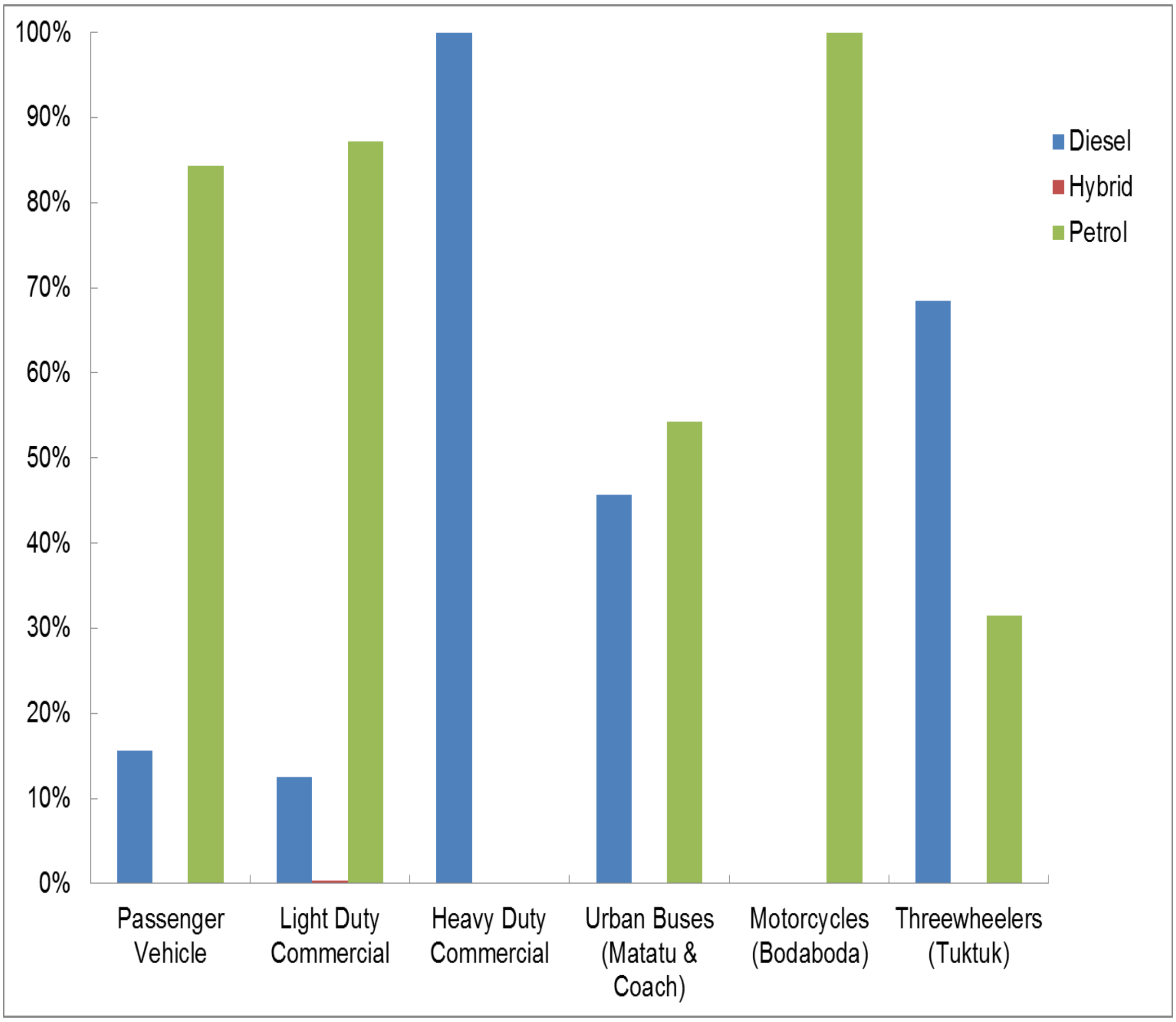

Figure S2: Fuel use for the different vehicle categories adjusted in accordance with vehicle classification used in this study for the year 2010. Source data: (Ministry of Transport Kenya, 2011; KNBS, 2013b, 2014b; ERC, 2015b).

In addition fuel quality and density for 2010 is shown in Table S3:

Table S 3: Fuel specifications in Kenya in 2010. Source data: (KEBS, 2007, 2010)

Fuel Specifications	Petrol	Diesel
Sulphur content (2010)	150 ppm	500 ppm
Density	716 kg/m^3	867 kg/m^3

S7.3 Activity Data

Average distance travelled per vehicle category is shown in Figure S3, this is calculated from an average daily mileage (Mbandi et al., in preparation) assuming 365 days a year.

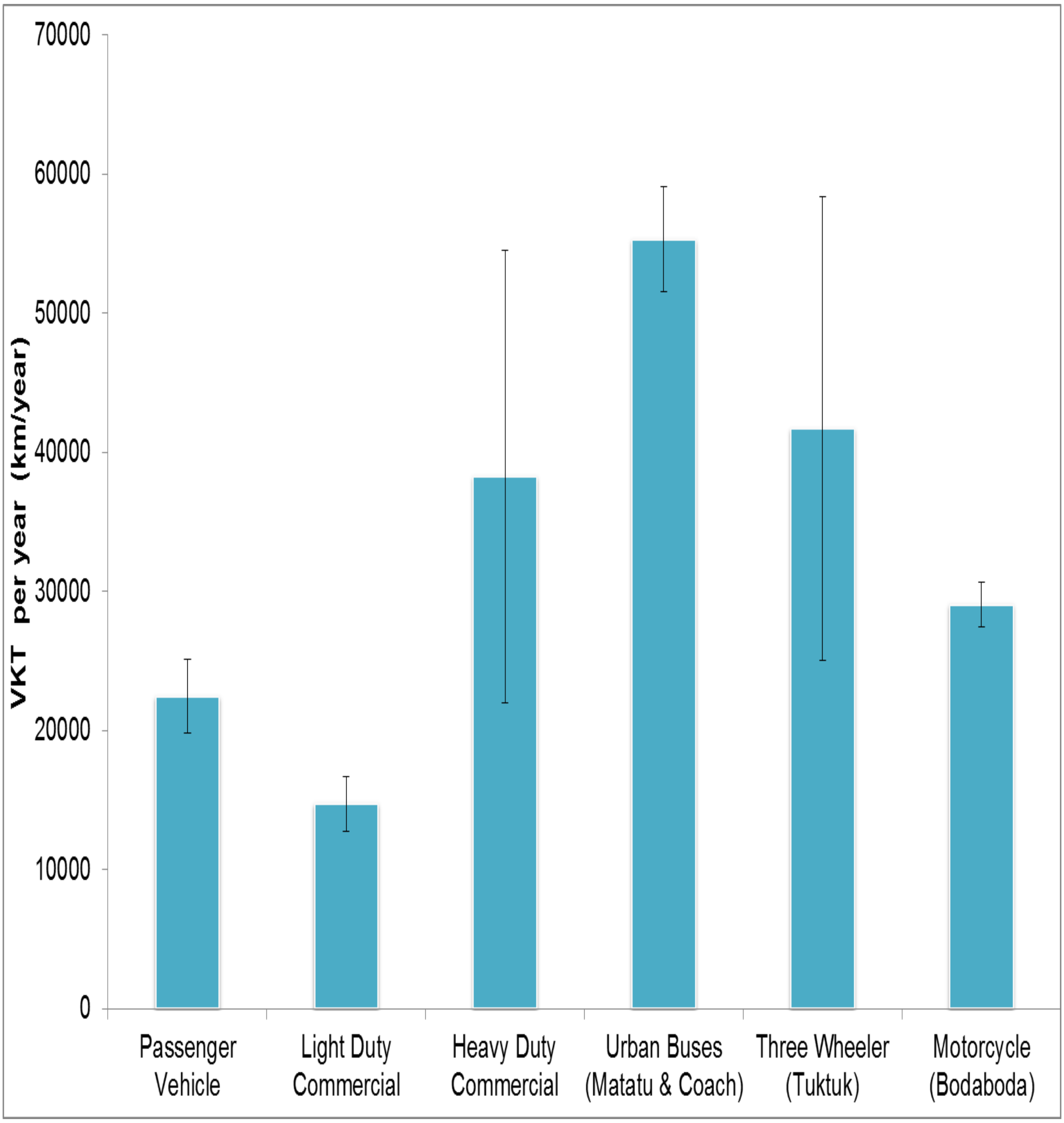

Figure S4: Vehicle activity for different categories in km/year with 95% confidence interval**.** Data source: (Mbandi et al., *in preparation*).

S7.4 Fuel Economy

The fuel economy, expressed as grams of fuel consumed for each km travelled, from each vehicle category is calculated from the density of the fuel (either petrol or diesel) together with the fuel economy (L/100 km) using the formula below and is presented in Figure S3:

$$FE\left(\frac{g}{km}\right) = 0.1 * FE\left(\frac{L}{km}\right) * (\rho_{petrol} * fraction_{petrol} + \rho_{diesel} * fraction_{diesel}$$

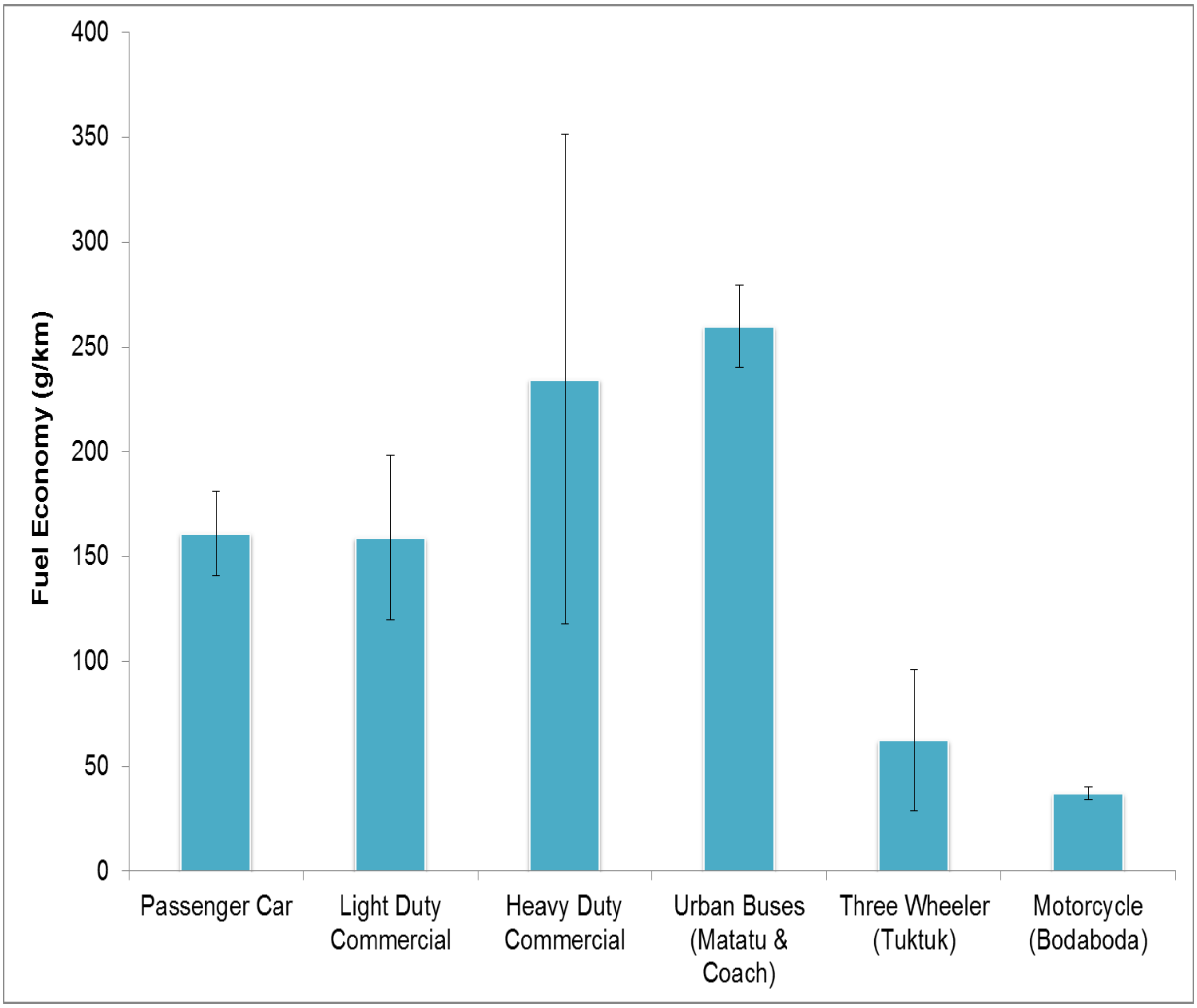

Figure S5: Fuel Economy for each vehicle category in g/km with 95% confidence interval calculated from (Mbandi et al., in preparation) and Equation shown above.

S7.5 Average distance travelled on unpaved roads as a percentage of the total

The average distance travelled on the unpaved roads is shown in Figure S6, the data for the paved and unpaved roads in the Nairobi Metropolitan Region (NMR) is sourced from Gachanja (2012), while nationwide data for similar is sourced from Ong'uti (2015) and Fukubayashi et al., (2016). Since 67% of registered vehicles are in-use in the NMR (Gachanja, 2012), the weighting of the roads from NMR are duly considered.

Table S6: Kenya's road network in kilometres paved and unpaved roads. Data source: (Gachanja, 2012; Ong'uti, 2015; Fukubayashi *et al.*, 2016)

	Paved (km)	Unpaved (km)	% unpaved	% of vehicles	Weighted % unpaved
Nairobi Metropolitan Region (NMR)	972	178	15.5%	67%	10%
Kenya (ex. NMR)	10218	149511	93.6%	33%	31%
Kenya (Total)	11190	149689	93.0%	100%	41%

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S7.6 Precipitation average for Kenya

The percentage of dry days, defined as less than 0.1 mm per day, is shown in Figure S6, the average for the year is 67.9% dry days.

Table S7: Precipitation average for the Kenya, by month for 2015. Wet days are days with greater than 0.1 mm rainfall per day and dry days are with less than 0.1 mm rainfall per day. Data source: (BBC, 2015).

Month	Wet days (>0.1mm) per month	How many days in month	% Dry days (<0.1mm) per month	Average precipitation (mm) per month
January	5	31	83.9%	38
February	6	28	78.6%	64
March	11	31	64.5%	125
April	16	30	46.7%	211
May	17	31	45.2%	158
June	9	30	70.0%	46
July	6	31	80.7%	15
August	7	31	77.4%	23
September	6	30	80.0%	31
October	8	31	75.0%	53
November	15	30	50.0%	109
December	11	31	64.5%	86
Average	10	30	68.0%	80

S7.7 Vehicle Emission factors

Table S8: Vehicle emission factors by vehicle category, fuel type and vehicle technology used for the BAU scenario. Data source: (ARAI, 2008; Ntziachristos *et al.*, 2013; Kouridis *et al.*, 2014). Reproduced with permission (SEI, 2015)

Mobile emissions from on-road vehicles (Detailed method).

Fuel	**Vehicle class** (For definition of EMEP/EEA vehicled classes see Table 2.1 at bottom of this worksheet)	**NO_X emission factor (g/km)**	**CO emission factor (g/km)**	**NMVOC emission factor (g/km)**	**NH_3 emission factor (g/km)**	**PM_{10} emission factor (g/km)**	**$PM_{2.5}$ emission factor (g/km) = PM10 emission factors)**	**Unpaved road dust (PM_{10}) emission factor in dry weather (g/km)**	**Unpaved road ($PM_{2.5}$) emissions factor (g/km)**	**BC emission factor (% of $PM_{2.5}$)**	**OC emission factor (OC/BC ratio)**
Fuel		**Default***	**Default***	**Default***	**Default***	**Default***	**Default*** [l]	**Default** [m]	**Default** [n]	**Default** [o]	**Default** [o]
Gasoline	Passenger cars (Uncontrolled) [a]	2.09[a]	18.9[a]	2.41[a]	0.10[a]	0.0029[a]	0.0029[a]	126	19	2	37.7
Gasoline	Passenger cars (Moderate control) [d]	1.29	6.49	0.29	0.002	0.0022	0.0022	126	19	30	1.79
Gasoline	Passenger cars (Euro I) [e]	0.53	3.92	0.53	0.0922	0.0022	0.0022	126	19	25	1.92
Gasoline	Passenger cars (Euro 2) [e]	0.255	2.04	0.251	0.1043	0.0022	0.0022	126	19	25	1.92
Gasoline	Passenger cars (Euro 3) [e]	0.119	1.82	0.119	0.0342	0.0011	0.0011	126	19	15	2.31
Gasoline	Passenger cars (Euro 4) [e]	0.065	0.62	0.065	0.0342	0.0011	0.0011	126	19	15	2.31
Gasoline	Passenger cars (Euro 5) [e]	0.065	0.62	0.065	0.0123	0.0014	0.0014	126	19	15	2.31
Gasoline	Passenger cars (Euro 6) [e]	0.065	0.62	0.065	0.0123	0.0014	0.0014	126	19	15	2.31
Gasoline	Light-commercial vehicles (Conventional) [i]	3.09	25.5	3.44	0.0025	0.0023	0.0023	225	34	30	1.79
Gasoline	Light-commercial vehicles (Euro 1) i	0.563	8.82	0.614	0.0758	0.0023	0.0023	225	34	25	1.92
Gasoline	Light-commercial vehicles (Euro 2) i	0.23	5.89	0.304	0.091	0.0023	0.0023	225	34	25	1.92
Gasoline	Light-commercial vehicles (Euro 3) i	0.129	5.05	0.189	0.0302	0.0011	0.0011	225	34	15	2.31
Gasoline	Light-commercial vehicles (Euro 4) i	0.064	2.01	0.128	0.0302	0.0011	0.0011	225	34	15	2.31
Gasoline	Light-commercial vehicles (Euro 5) i	0.064	1.30	0.096	0.0123	0.0014	0.0014	225	34	15	2.31
Gasoline	Light-commercial vehicles (Euro 6) i	0.064	1.30	0.096	0.0123	0.0012	0.0012	225	34	15	2.31
Gasoline	Heavy duty (Conventional) [c]	6.6	59.5	5.25	0.0019	0.0023	0.0023	450	68	30 [H]	1.79 [H]
Gasoline	Motorcycles (2-stroke) (Uncontrolled)[a]	0.375[a]	23.2[a]	12.8[a]	0.0023[a]	0.21[a]	0.21[a]	36	5	10	6.90
Gasoline	Motorcycles (2-stroke) (Moderate control) [f]	0.067	24.3	9.97	0.0019	0.16	0.16	36	5	10	6.90
Gasoline	Motorcycles (2-stroke) (Mot-Euro 1)	0.028	16.3	5.82	0.0019	0.064	0.064	36	5	20	3.08
Gasoline	Motorcycles (2-stroke) (Mot-Euro 2)	0.104	11.2	1.84	0.0019	0.032	0.032	36	5	20	3.08
Gasoline	Motorcycles (2-stroke) (Mot-Euro 3)	0.280	2.73	0.806	0.0019	0.0096	0.0096	36	5	20	3.08
Gasoline	Motorcycles (4-stroke) (Uncontrolled)[a]	0.375[a]	23.2[a]	12.8[a]	0.0023[a]	0.21[a]	0.21[a]	36	5	15	4.30
Gasoline	Motorcycles (4-stroke) (Moderate control) [g]	0.233	25.7	1.68	0.0019	0.014	0.014	36	5	15	4.30
Gasoline	Motorcycles (4-stroke) (Mot-Euro 1)	0.477	13.8	1.19	0.0019	0.014	0.014	36	5	25	2.31
Gasoline	Motorcycles (4-stroke) (Mot-Euro 2)	0.317	7.17	0.918	0.0019	0.0035	0.0035	36	5	25	2.31
Gasoline	Motorcycles (4-stroke) (Mot-Euro 3)	0.194	3.03	0.541	0.0019	0.0035	0.0035	36	5	25	1.92
Gasoline	3-Wheelers (2-stroke) (uncontrolled)	0.375[b]	23.2[b]	12.8[b]	0.0023[b]	0.21[b]	0.21[b]	90	14	10	6.90
Gasoline	3-Wheelers (2-stroke) (Medium control)	0.30 [A]	3.15 [A]	6.04 [A]	0.0023[a]	0.11[A]	0.11[A]	90	14	10	6.90
Gasoline	3-Wheelers (2-stroke) (Bharat 1 ≡ Euro 1)	0.20 [B]	1.37 [B]	2.53 [B]	0.0023[a]	0.045 [B]	0.045 [B]	90	14	20	3.08
Gasoline	3-Wheelers (2-stroke) (Bharat 2 ≡ Euro 2)	0.16 [C]	1.15 [C]	1.63 [C]	0.0023[a]	0.043 [C]	0.043 [C]	90	14	20	3.08
Gasoline	3-Wheelers (4-stroke) (Bharat 1 ≡ Euro 1)	0.61 [B]	4.47 [B]	1.57 [B]	0.0023[a]	0.011[B]	0.011[B]	90	14	25	2.31
Gasoline	3-Wheelers (4-stroke) (Bharat 2 ≡ Euro 2)	0.53 [C]	2.29 [C]	0.77 [C]	0.0023[a]	0.015 [C]	0.015 [C]	90	14	25	2.31
Gasoline	**Total for gasoline**										
Diesel	3-Wheelers (Moderate control)	0.93 [A]	9.16 [A]	0.63 [A]	0.001	0.782 [A]	0.782 [A]	90	14	55	0.54
Diesel	3-Wheelers (Bharat 1 ≡ Euro 1)	0.69 [B]	2.09 [B]	0.16 [B]	0.001	0.347 [B]	0.347 [B]	90	14	70	0.31
Diesel	3-Wheelers (Bharat 2 ≡ Euro 2)	0.51 [C]	0.41 [C]	0.14 [C]	0.001	0.091 [C]	0.091 [C]	90	14	80	0.18
Diesel	Passenger cars (Conventional) [h]	0.546	0.688	0.159	0.001	0.2209	0.2209	126	19	55	0.54
Diesel	Passenger cars (Euro 1) [h]	0.690	0.414	0.047	0.001	0.0842	0.0842	126	19	70	0.31
Diesel	Passenger cars (Euro 2) [h]	0.716	0.296	0.035	0.001	0.0548	0.0548	126	19	80	0.18
Diesel	Passenger cars (Euro 3) [h]	0.773	0.089	0.02	0.001	0.0391	0.0391	126	19	85	0.12
Diesel	Passenger cars (Euro 4) [h]	0.58	0.092	0.014	0.001	0.0314	0.0314	126	19	87	0.1
Diesel	Passenger cars (Euro 5) [h]	0.61	0.04	0.008	0.0019	0.0021	0.0021	126	19	10	3.85
Diesel	Passenger cars (Euro 6) [h]	0.21	0.049	0.008	0.0019	0.0015	0.0015	126	19	20	1.54
Diesel	Light-commercial vehicles (Conventional) i	1.66	1.34	0.133	0.0012	0.356	0.356	225	34	55	0.54
Diesel	Light-commercial vehicles (Euro 1) i	1.22	0.577	0.141	0.0012	0.117	0.117	225	34	70	0.31
Diesel	Light-commercial vehicles (Euro 2) i	1.22	0.577	0.149	0.0012	0.117	0.117	225	34	80	0.18
Diesel	Light-commercial vehicles (Euro 3) i	1.03	0.473	0.094	0.0012	0.0783	0.0783	225	34	85	0.12
Diesel	Light-commercial vehicles (Euro 4) i	0.831	0.375	0.035	0.0012	0.0409	0.0409	225	34	87	0.1
Diesel	Light-commercial vehicles (Euro 5) i	0.622	0.075	0.035	0.0019	0.001	0.001	225	34	10	3.85
Diesel	Light-commercial vehicles (Euro 6) i	0.221	0.075	0.035	0.0019	0.0009	0.0009	225	34	20	1.54
Diesel	Heavy-duty vehicles (Conventional) [j]	8.92	2.13	0.776	0.0029	0.333	0.333	450	68	50	0.154
Diesel	Heavy-duty vehicles (HD Euro I) [j]	5.31	1.020	0.326	0.0029	0.129	0.129	450	68	65	0.154
Diesel	Heavy-duty vehicles (HD Euro II) [j]	5.5	0.902	0.207	0.0029	0.061	0.061	450	68	65	0.154
Diesel	Heavy-duty vehicles (HD Euro III) [j]	4.3	0.972	0.189	0.0029	0.0566	0.0566	450	68	70	0.154
Diesel	Heavy-duty vehicles (HD Euro IV) [j]	2.65	0.071	0.008	0.0029	0.0106	0.0106	450	68	75	0.154
Diesel	Heavy-duty vehicles (HD Euro V) [j]	1.51	0.071	0.008	0.011	0.0106	0.0106	450	68	75	0.154
Diesel	Heavy-duty vehicles (HD Euro VI) [j]	0.291	0.071	0.008	0.011	0.0005	0.0005	450	68	15	2.31
Diesel	Urban Buses (Conventional) [j]	16.5	5.710	1.990	0.0029	0.909	0.909	450	68	50	0.154
Diesel	Urban buses (HD Euro I) [k]	10.1	2.710	0.706	0.0029	0.479	0.479	450	68	65	0.154
Diesel	Urban buses (HD Euro II) [k]	10.7	2.440	0.463	0.0029	0.22	0.22	450	68	65	0.154
Diesel	Urban buses (HD Euro III) [k]	9.38	2.670	0.409	0.0029	0.207	0.207	450	68	70	0.154
Diesel	Urban buses (HD Euro IV) [k]	5.42	0.223	0.220	0.0029	0.0462	0.0462	450	68	75	0.154
Diesel	Urban buses (HD Euro V) [k]	3.09	0.223	0.220	0.0029	0.0462	0.0462	450	68	75	0.154
Diesel	Urban buses (HD Euro VI) [k]	0.597	0.223	0.220	0.0029	0.0023	0.0023	450	68	15	0.231

CNG	3-wheeler (Bharat 1 ≡ Euro 1)	0.50 [B]	1.00 [B]	0.26 [B]	0.034	0.015 [B]	0.015 [B]	90	14		
CNG	3-wheeler Retrofit (Bharat 1 ≡ Euro 1)	0.19 [B]	0.69 [B]	2.06 [B]	0.034	0.118 [B]	0.118 [B]	90	14		
CNG	Passenger car retrofit (moderate control)	0.53 [A]	0.85 [A]	0.79 [A]	0.034	0.001 [A]	0.001 [A]	126	19		
CNG	Passenger car retrofit (Bharat 1 = Euro 1)	0.01 [B]	0.60 [B]	0.36 [B]	0.034	0.002 [B]	0.002 [B]	126	19		
CNG	Passenger car (Euro 4 and later)	0.056	0.616	0.035	0.034	0.0011	0.0011	126	19		
CNG	Urban Bus (HD Euro I)	16.5	8.4	0.371	n.a.	0.02	0.02	450	68		
CNG	Urban Bus (HD Euro II)	15	2.7	0.313	n.a.	0.01	0.01	450	68		
CNG	Urban Bus (HD Euro III)	10	1	0.052	n.a.	0.01	0.01	450	68		
CNG	**Total for CNG**										
LPG	3-wheeler Retrofit (Moderate control) [A]	0.05 [A]	7.2 [A]	5.08 [A]	0.002 [E]	0.171 [A]	0.171 [A]	90	14		
LPG	3-wheeler Retrofit (Bharat 1 ≡ Euro 1)	0.04 [B]	1.70 [B]	1.03 [B]	0.088 [E]	0.130 [B]	0.130 [B]	90	14		
LPG	Passenger cars (Conventional)	2.36	6.832	1.05	0.0020	0.0022	0.0022	126	19		
LPG	Passenger cars (Euro 1)	0.414	3.57	0.723	0.0880	0.0022	0.0022	126	19		
LPG	Passenger cars (Euro 2)	0.18	2.48	0.342	0.1007	0.0022	0.0022	126	19		
LPG	Passenger cars (Euro 3)	0.09	1.79	0.120	0.0338	0.0011	0.0011	126	19		
LPG	Passenger cars (Euro 4)	0.056	0.62	0.100	0.0338	0.0011	0.0011	126	19		
LPG	Passenger cars (Euro 5)	0.056	0.62	0.100	0.0338	0.0011	0.0011	126	19		
LPG	Passenger cars (Euro 6)	0.056	0.62	0.100	0.0338	0.0011	0.0011	126	19		
LPG	Light-duty vehicles (Uncontrolled)	2.1 [F]	8.0 [F]	3.5 [F]	0.002 [E]	0.0022 [E]	0.0022 [E]	225	34		
LPG	Light-duty vehicles (Good control - Euro-I)	0.05 [F]	0.3 [F]	0.25 [F]	0.088 [E]	0.0022 [E]	0.0022 [E]	225	34		
LPG	Heavy-duty vehicles (Uncontrolled)	5.7 [G]	24 [G]	8 [G]	0.004 [E]	0.0044 [E]	0.0044 [E]	450	68		
LPG	Heavy-duty vehicles (Good contro)	2.6 [G]	1.0 [G]	0.7 [G]	0.176 [E]	0.0044 [E]	0.0044 [E]	450	68		
LPG	**Total for LPG**										
Total											

* Emission factors are Tier 2 exhaust emission factors from EMEP/EEA (2013), Tables 3-16 to 3-25, unless otherwise indicated.

[a] Uncontrolled EFs = Tier 1 maximum value from EMEP/EEA (2013) converted assuming fuel economy from Table 3-14, EMEP/EEA, 2013

[b] Assume = Motorcycle 2-stroke (uncontrolled)

[c] Heavy duty vehicle, Gasoline, >3.5 t weight.

[d] Emission factors for Gasoline passenger cars (1.4 - 2.0 L engine capacity), Open loop technology (from EMEP/EEA (2013), Tables 3-16 and 3-17)

[e] Emission factors for Gasoline passenger cars (1.4 - 2.0 L engine capacity) from EMEP/EEA (2013) Tier 2 exhaust emission factors, Tables 3-16 and 3-17.

[f] Emission factors for 2-stroke motorcycles (>50 cm^3), 'Conventional' technology (from EMEP/EEA (2013), Tables 3-24 and 3-25)

[g] Emission factors for 4-stroke motorcycles (250 - 750 cm^3), 'Conventional' technology (from EMEP/EEA (2013), Tables 3-24 and 3-25)

[h] Emission factors for Diesel passenger cars (1.4 - 2.0 L engine capacity) from EMEP/EEA (2013) Tier 2 exhaust emission factors, Tables 3-16 and 3-17.

[i] Emission factors for Light Commercial Vehicles (<3.5 t weight) from EMEP/EEA (2013) Tier 2 exhaust emission factors, Tables 3-18 and 3-19.

[j] Emission factors for Heavy Duty Vehicles (7.5 - 16 t weight) from EMEP/EEA (2013) Tier 2 exhaust emission factors, Tables 3-20 and 3-21

[k] Urban buses standard - vehicles used for the carriage of passengers and comprising more than eight seats in addition to the driver's seat

[l] Assume PM2.5 EF = PM10 EF

[m] Derived from Gillies et.al. (2005) for unpaved rural roads in dry weather

[n] Assume $PM_{2.5}$ factor is 15% of PM_{10} factor (USEPA, 1995)

[o] EMEP/EEA (2013) Tier 3 fraction BC (%) and Organic matter (OM) to BC ratio (Table 3-114) assuming OM = 1.3xOC

[A] ARAI (2008) value for Indian fleet 1996-2000

[B] ARAI (2008) value for Indian fleet post 2000 (Bharat 1 ≡ Euro 1)

[C] ARAI (2008) value for Indian fleet post 2005 (Bharat 2 ≡ Euro 2)

[E] Assume LDV = passenger car; HDV = 2 x passenger car

[F] IPCC (1996) default EF for US LPG passenger cars

[G] IPCC (1996) default EF for US LPG uncontrolled heavy duty vehicles with stoichiometric engine

[H] Assume = LCV (Conventional)

S7.8 Other sectors simple (top down) inventory

The general overview of the methods, data and data sources from the other sectors is described in the table below and the divisions follow the 2006 IPCC guidelines (IPCC, 2006). To account for emissions from all sectors data input is divided into demand, transformation and non-energy sectors.

The demand sector includes fuel combustion activities from 'own use' in the energy industries (e.g. refinery gas in oil refineries), manufacturing and construction, commercial and public services, residential and agriculture/forestry/fishing. Data for the demand category for Kenya in 2010 was obtained from the International Energy Agency (IEA) database (IEA, 2012b), the unit was energy released from the combustion of the various fuels consumed in kilotonnes of oil equivalent for (ktoe)The agriculture subsector data were obtained from the UN Food and Agriculture Organization (FAO): animal numbers, area harvested, crops processed, crops harvested, fertilizer consumption and production, forestry production and savannah fires (FAO, 2017).

Demand
Energy Industry own use
Manufacturing and construction
Brick kilns
Residential
Commercial and public services
Agriculture and Fishing

Transformation
Electricity generation
Charcoal making

Non-Energy
Fugitive (coke, oil exploration & production), oil refining, NMVOCs from distribution & handling, gas production process and distribution, CH4 from coal mining
Transport dust
Industrial process fugitive
Solvents and other product use
Agriculture-enteric fermentation
Agriculture-residue burning
Methane from rice cultivation
Savannah burning
Waste incineration
Ammonia from excreta
Methane from domestic water
Aviation

Figure S9: Structure of the non-transport sector emissions divided into key assumptions, transformation, demand and non-energy sectors.

The transformation sector generates energy-carriers that are then consumed by the demand sectors above. This includes electricity generation and charcoal production, data sources (IEA, 2012b).

Non-Energy sector emissions are from activities that are not fuel combustion related. These include industrial and manufacturing processes such as cement manufacture, fugitive emissions from coke production, oil and gas exploration and production, non-methane volatile organic compounds (NMVOCs) from distribution and handling of fuel in refinery dispatch stations, deports and service station as well as from gas distribution, and methane from coal mining and fugitive emissions from industrial processes. These fugitive emissions differ from process emissions for example accounted for in the demand sector under manufacturing, because they are emissions outside of the manufacturing process such as chemical reaction or combustion. Also, included in the non-energy sectors are emissions from agricultural processes such as open-burning of crop residues, and methane from cultivation of rice and from enteric fermentation in livestock. Methane from municipal solid waste land-fill and methane and ammonia emissions from human waste as well as emissions from waste incineration emissions are included as well. Savannah fires were also a considered as they are an important component of emissions load for Kenya.

4.6.2 Section B: Building a Business as Usual (BAU) scenario

S7.9 Baseline setting BAU scenario for transport sector

Using data available (KNBS, 2013b, 2014b; World Bank, 2014) two variables: GDP per capita and the total number of vehicles from 1998-2013 was plotted against each other to determine the relation between these two variables for the purpose of predicting total number of vehicles for each vehicle category.

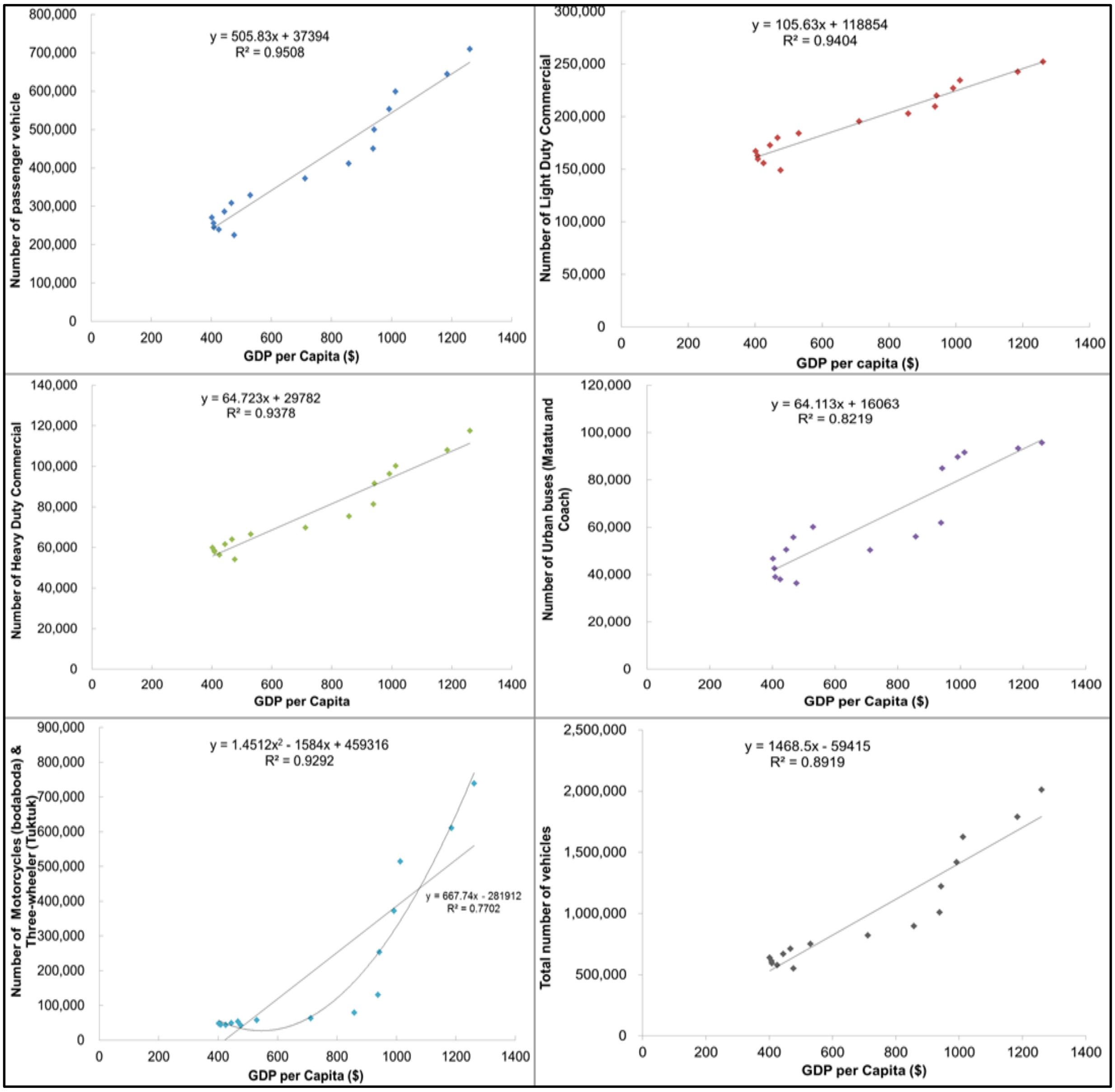

Figure S10: Relation between GDP per capita in US dollars ($) for Kenya between 1998-2013 data source (KNBS, 2013b, 2014b; World Bank, 2014)

4.6.3 Section C: Supplementary Results

S7.10 Emissions from all sectors

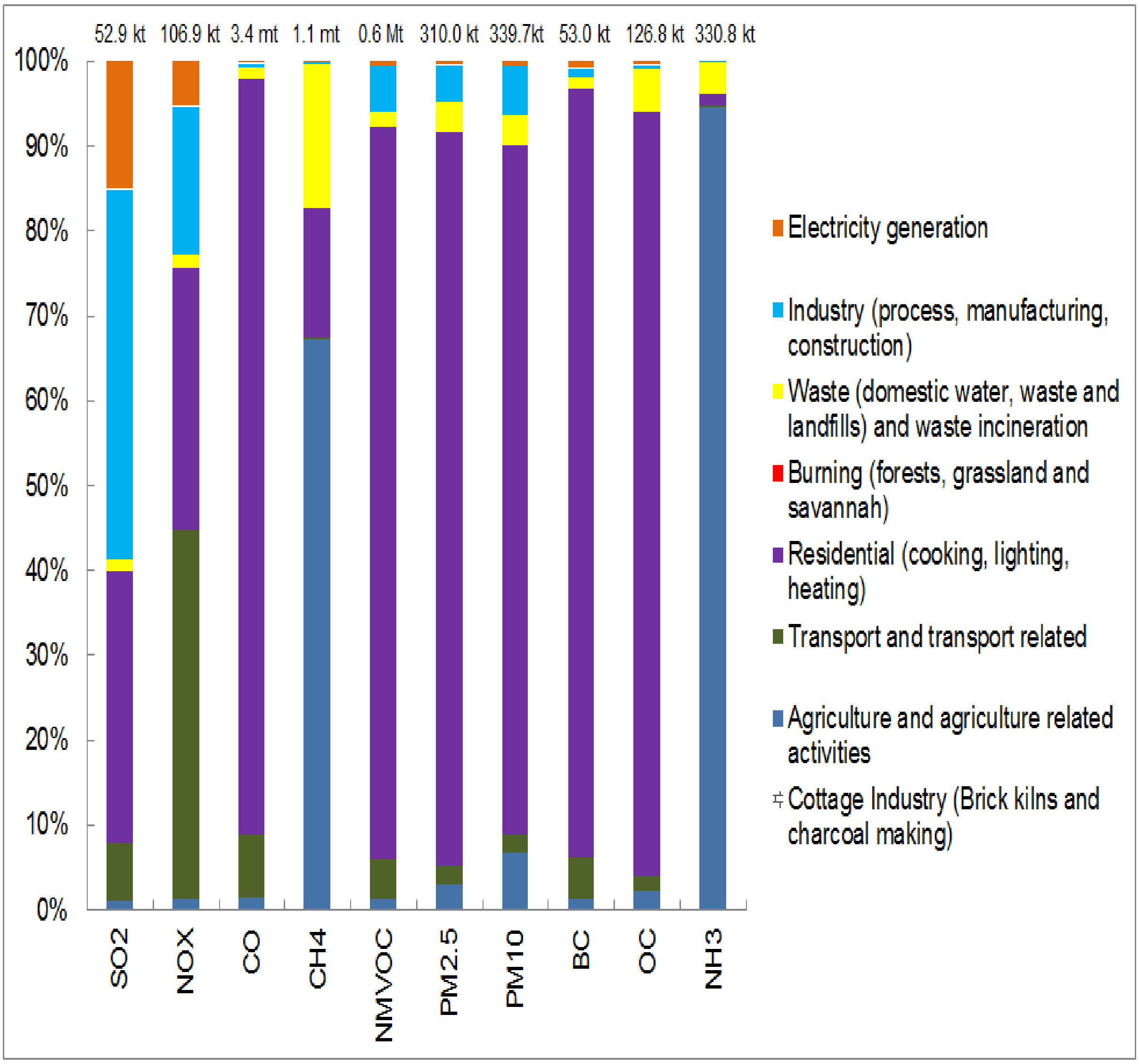

Figure S11: Emissions for all species from all sectors from ECLIPSE (IIASA, 2016)

S7.11 Emissions of road transport from BAU scenario

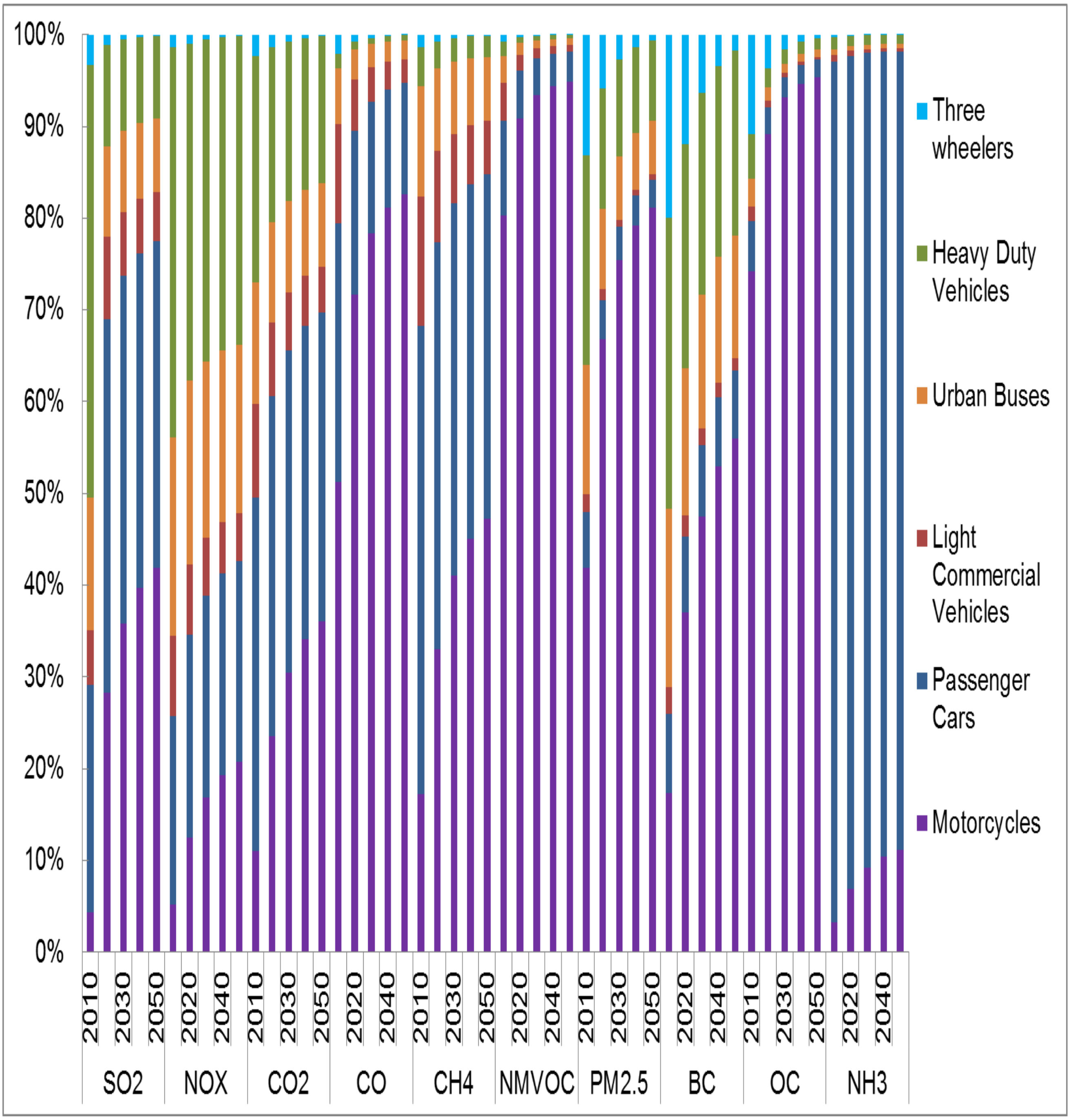

Figure S12: Road transport for BAU for all species

S7.12 Emissions of road transport from all the different scenarios

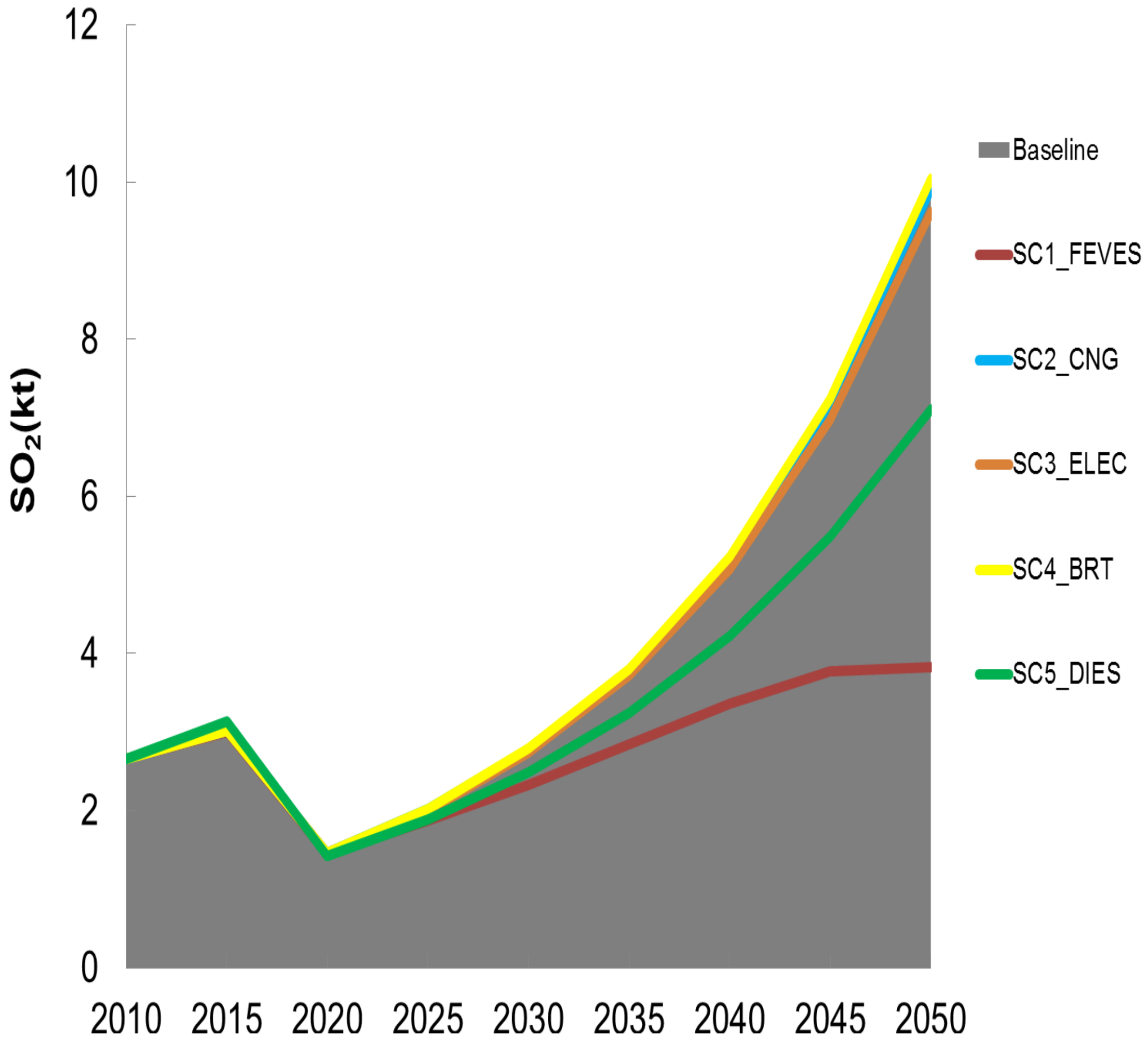

Figure S13: Road Transport SO2 (kt) emissions from all scenarios

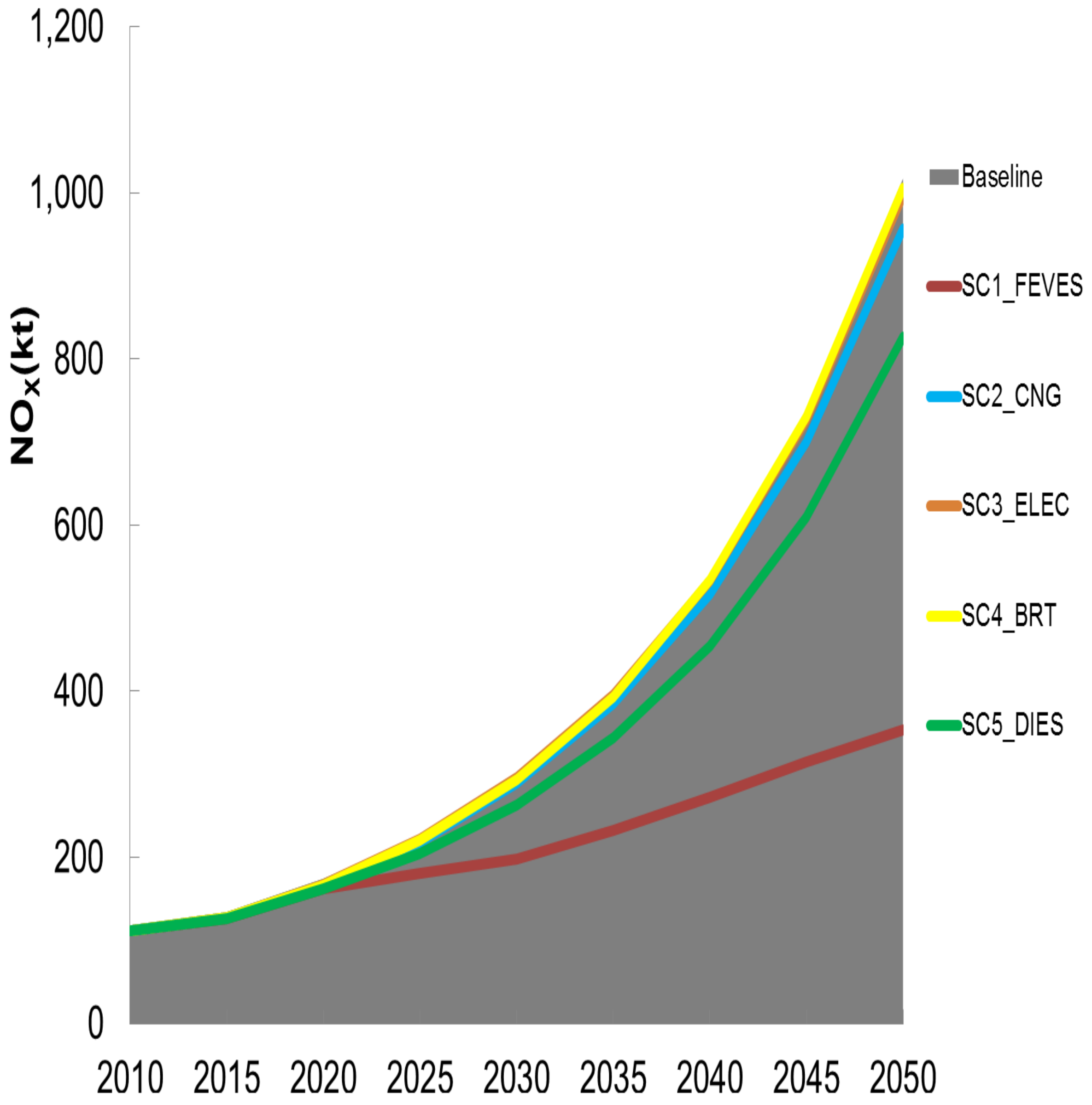

Figure S14: Road transport NOX emissions from all scenarios

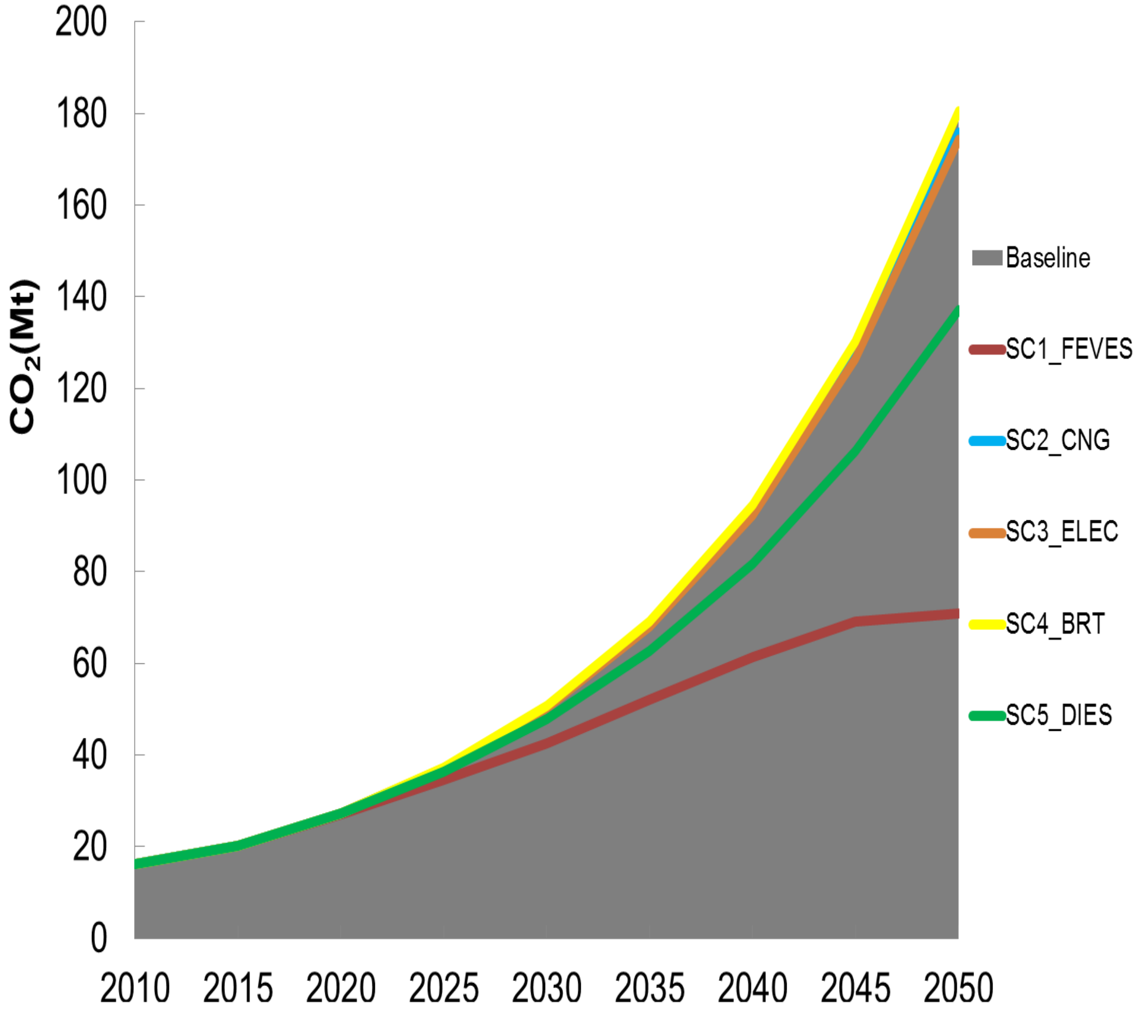

Figure S15: Road Transport CO2 (mt) emissions from all scenarios

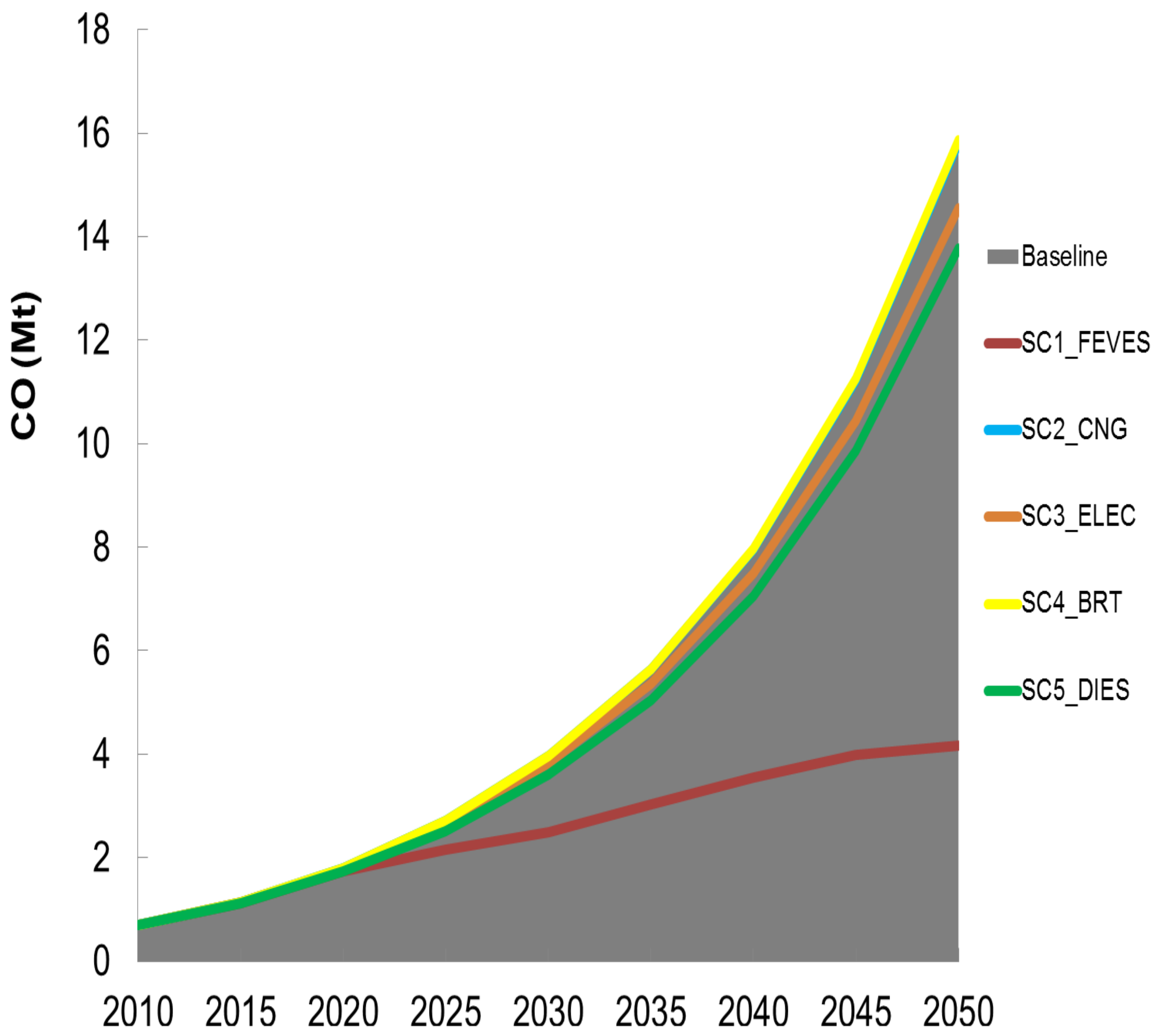

Figure S 16: Road Transport CO emissions (mt) from all scenarios

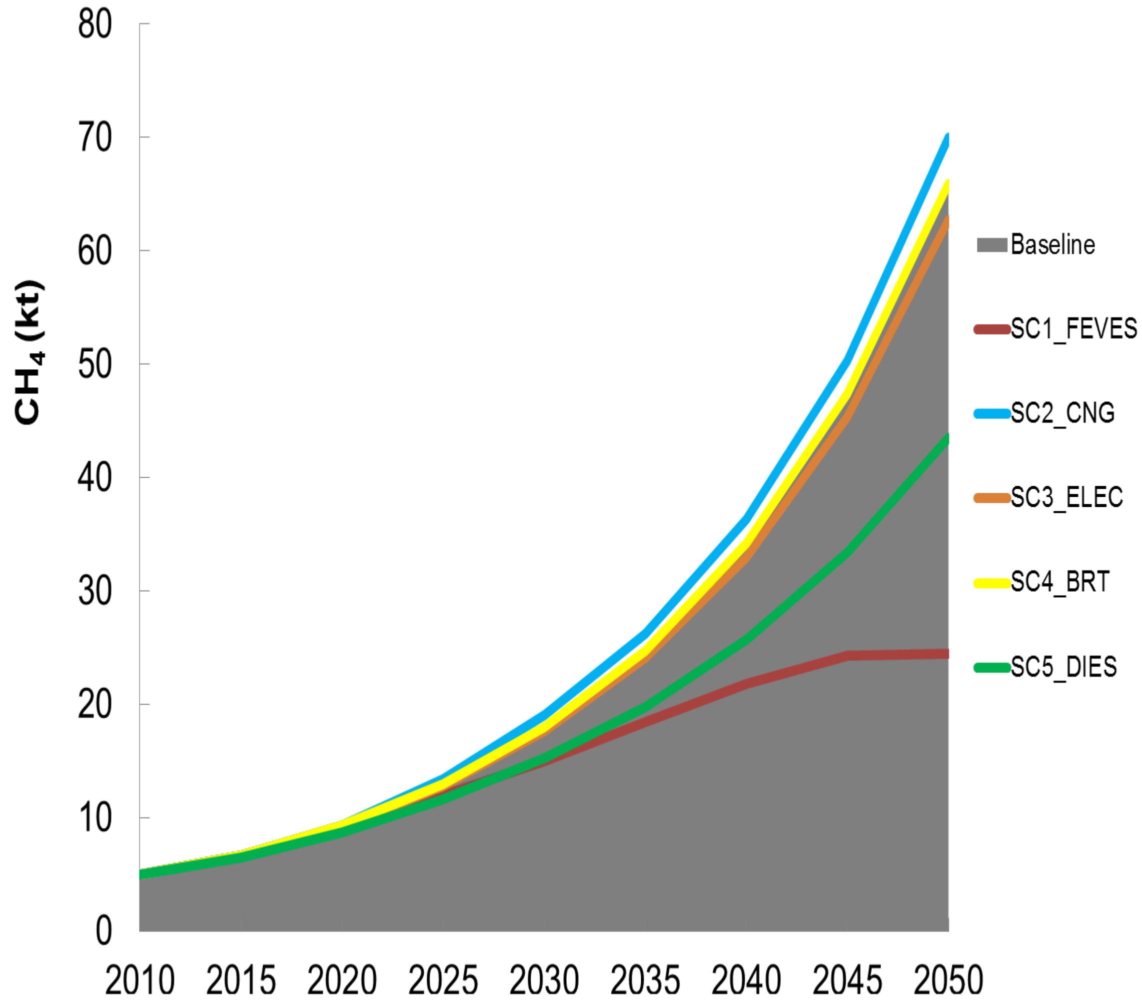

Figure S 17: Road Transport CH4 (kt) emissions from all scenarios

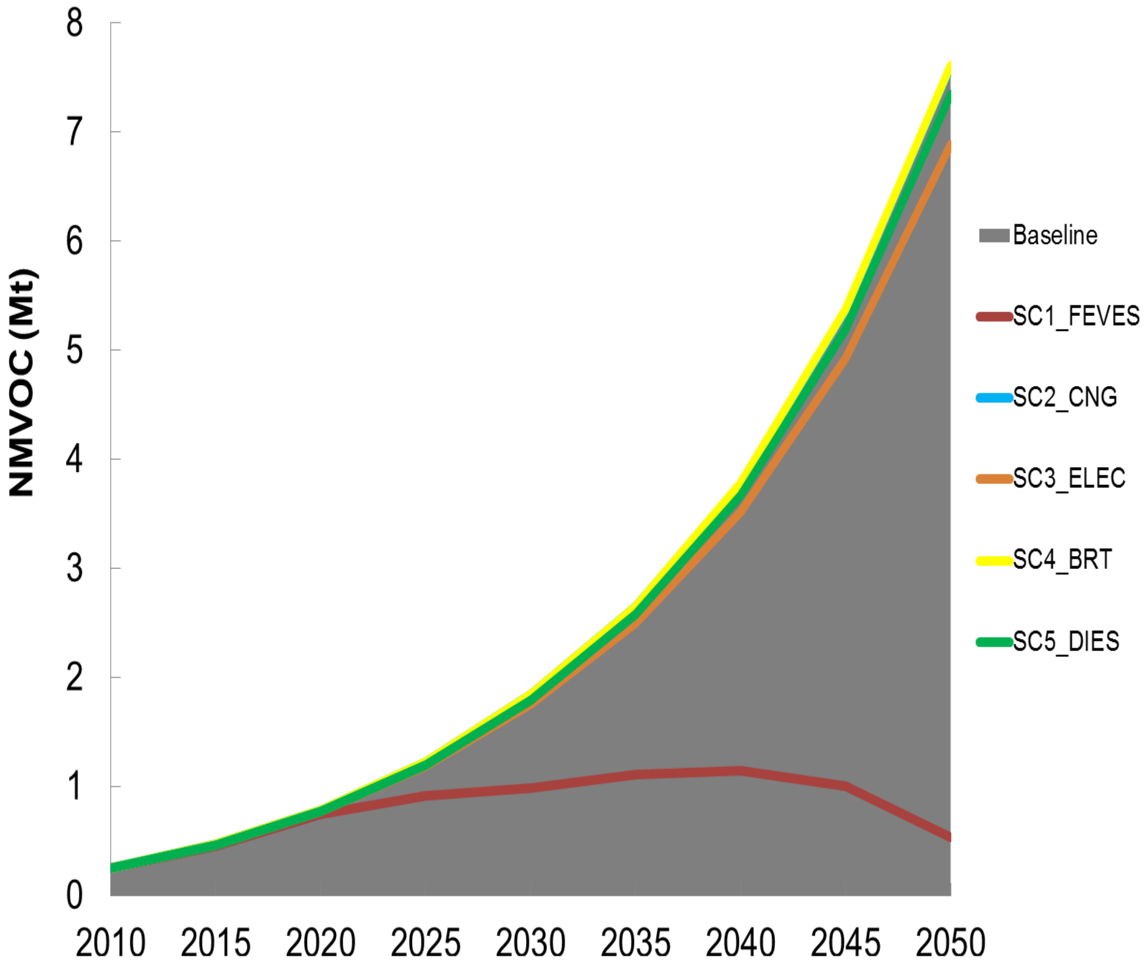

Figure S 18: Road Transport NMVOC (Mt) emissions from all scenarios

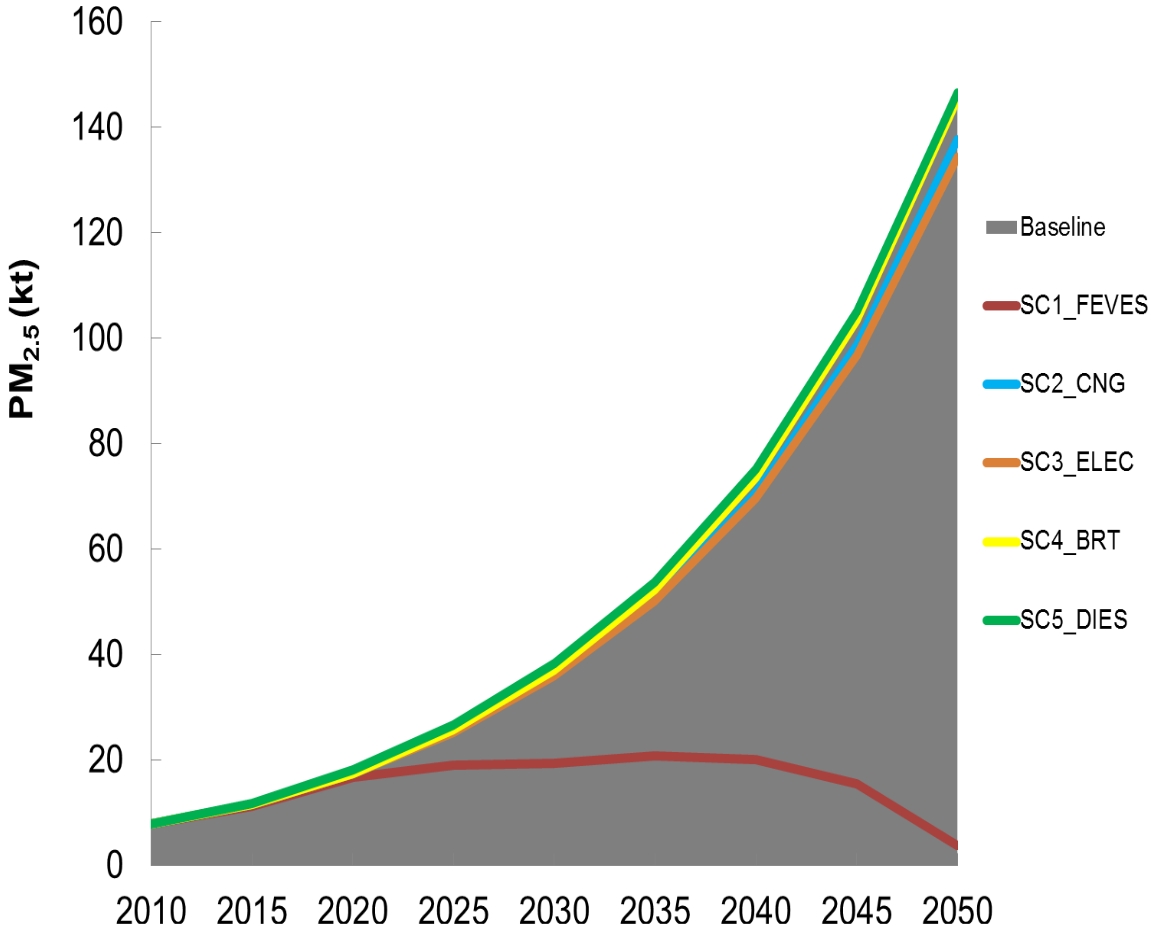

Figure S 19: Road Transport emissions PM2.5(kt) from all scenarios

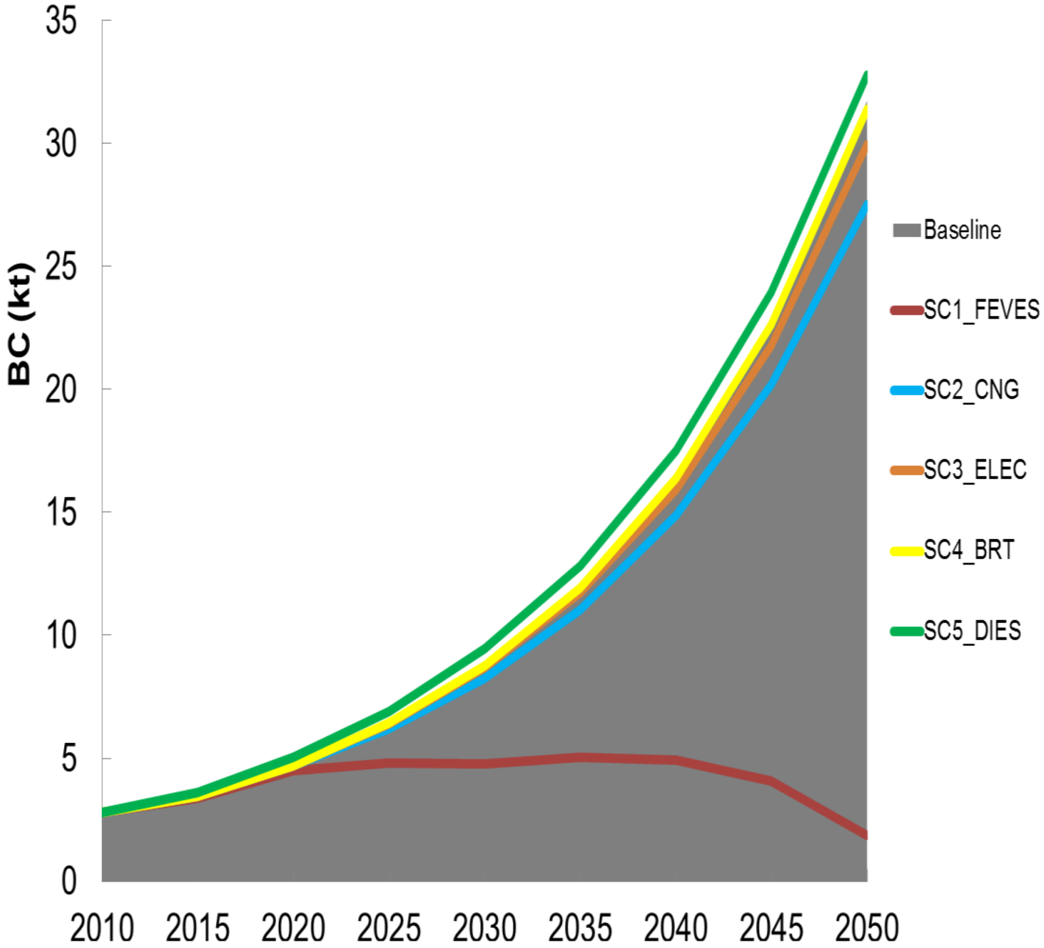

Figure S 20: Road Transport emissions BC (kt) from all scenarios

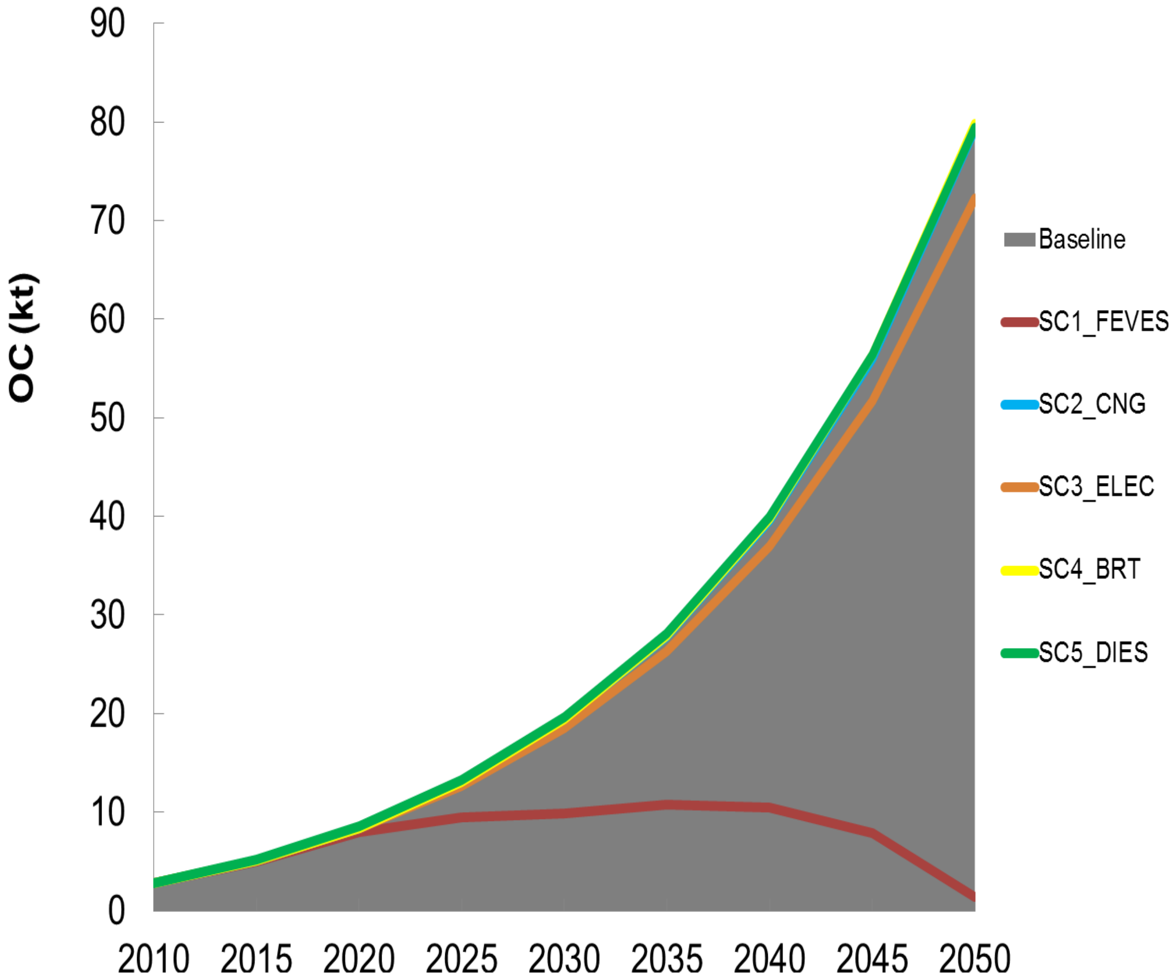

Figure S 21: Road Transport emissions OC (kt) from all scenarios

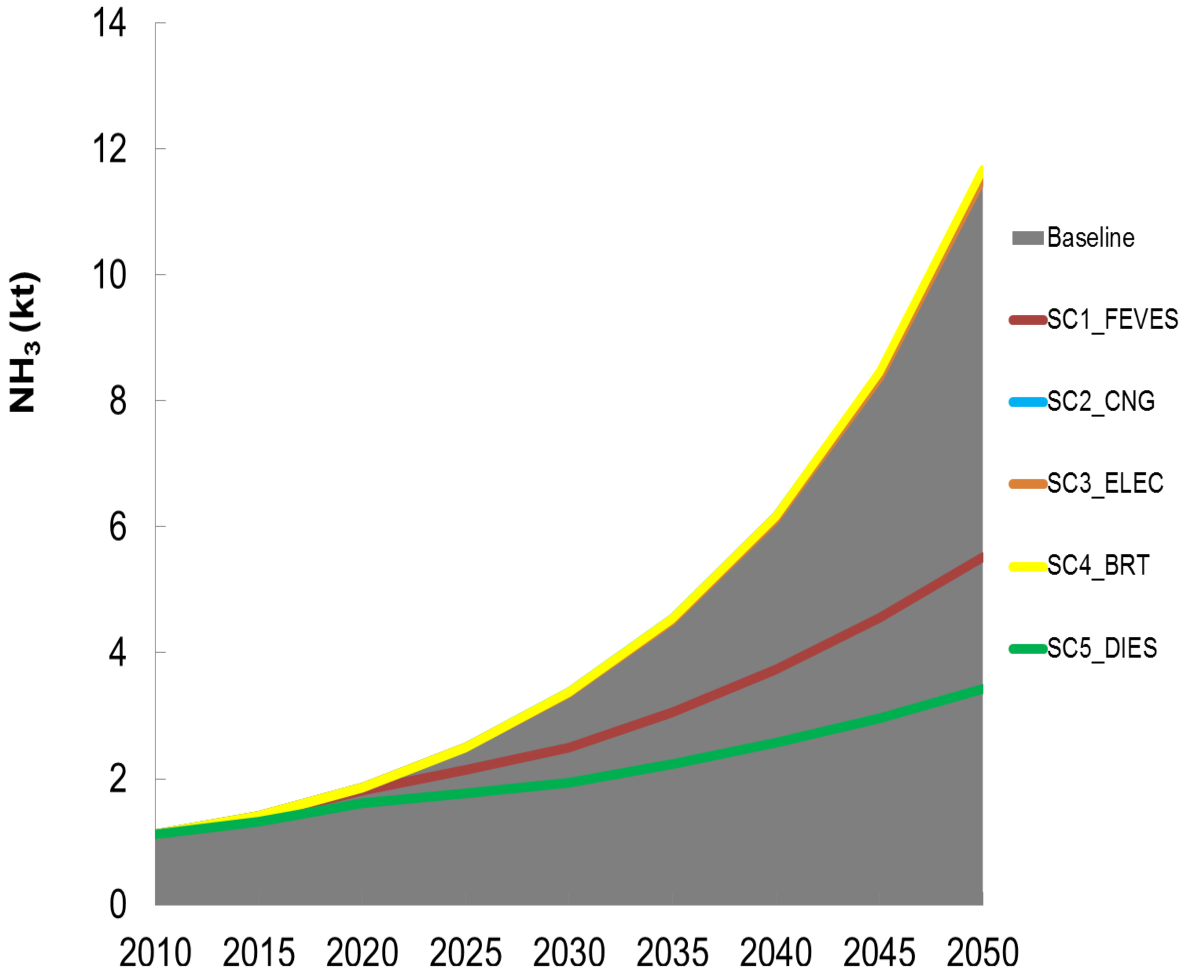

Figure S 22: Road Transport emissions NH_3 (kt) from all scenarios

S7.13 Effect of emissions of vehicle types from different scenarios

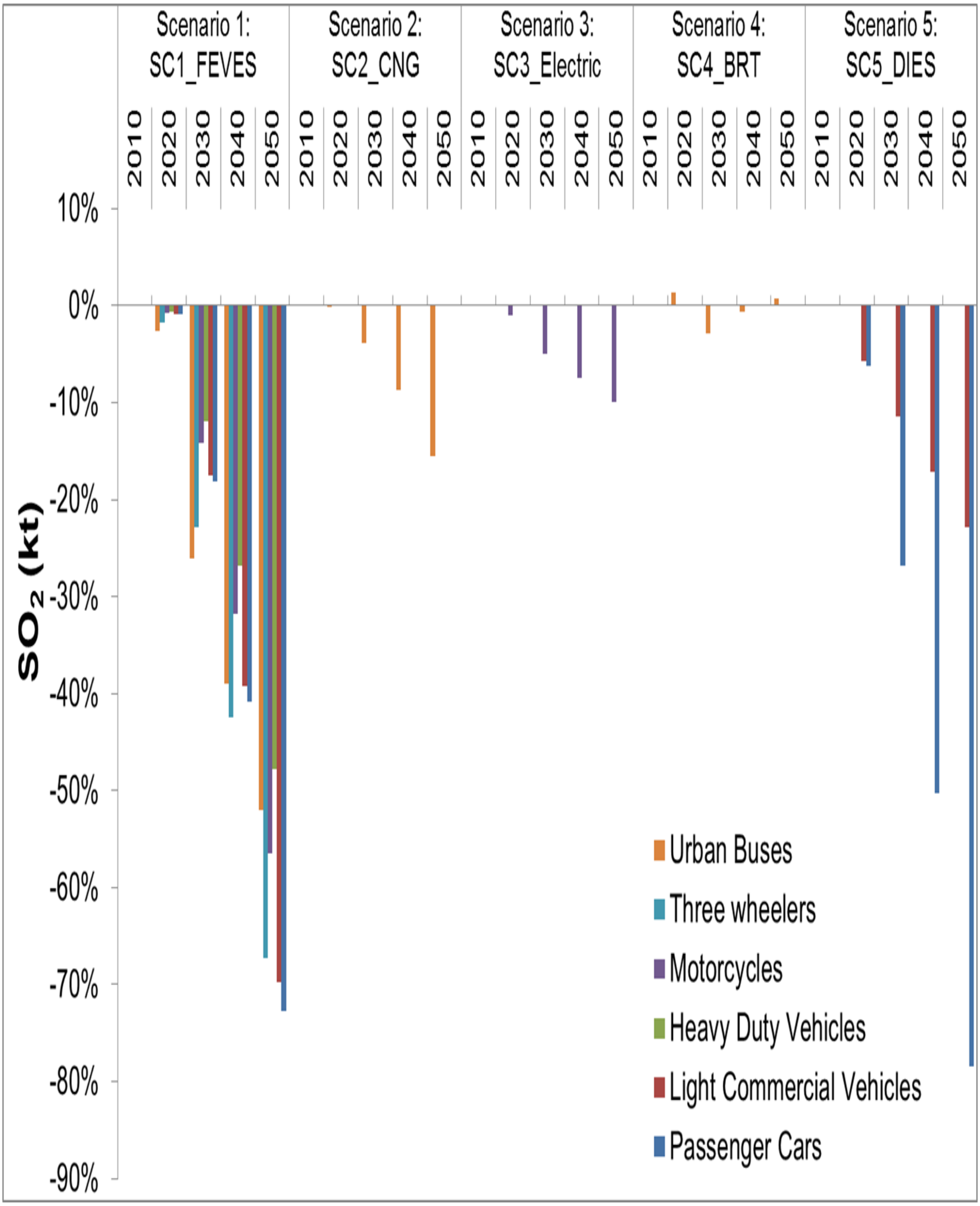

Figure S 23: SO_2 emission reductions compared to BAU for different vehicle types

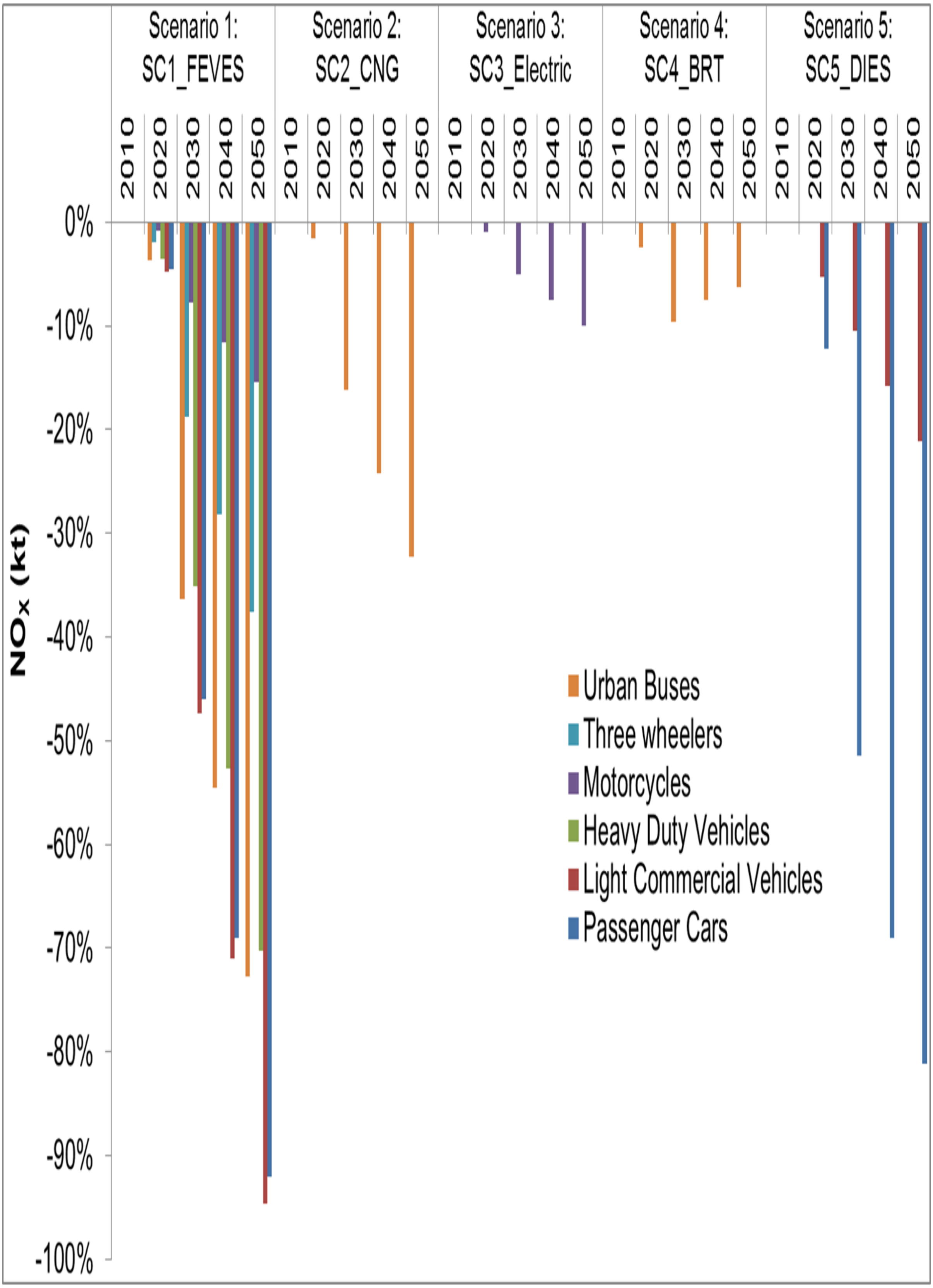

Figure S 24: NO_X emission reductions compared to BAU for different vehicle types

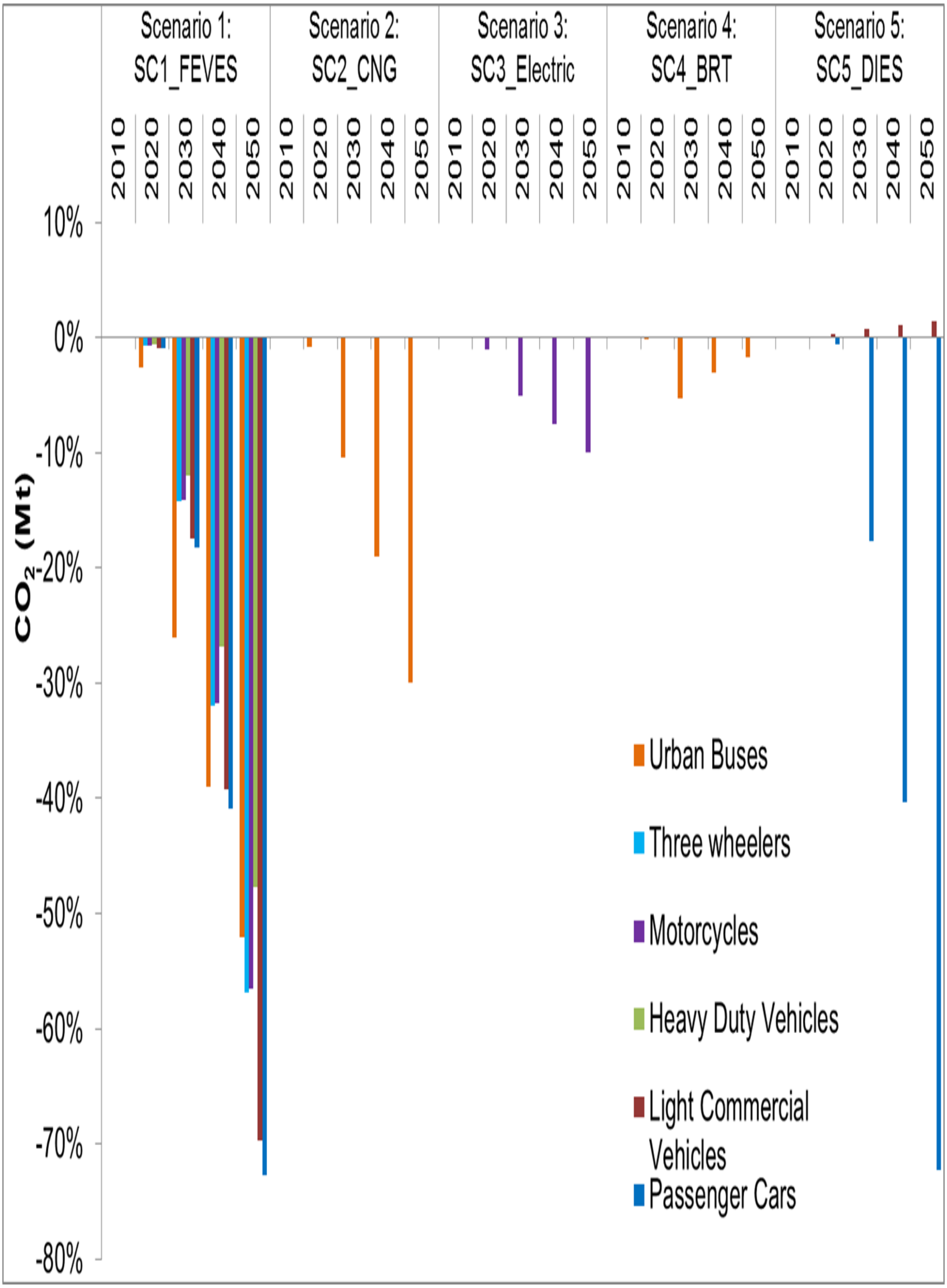

Figure S 25: CO_2 emission reductions compared to BAU for different vehicle types

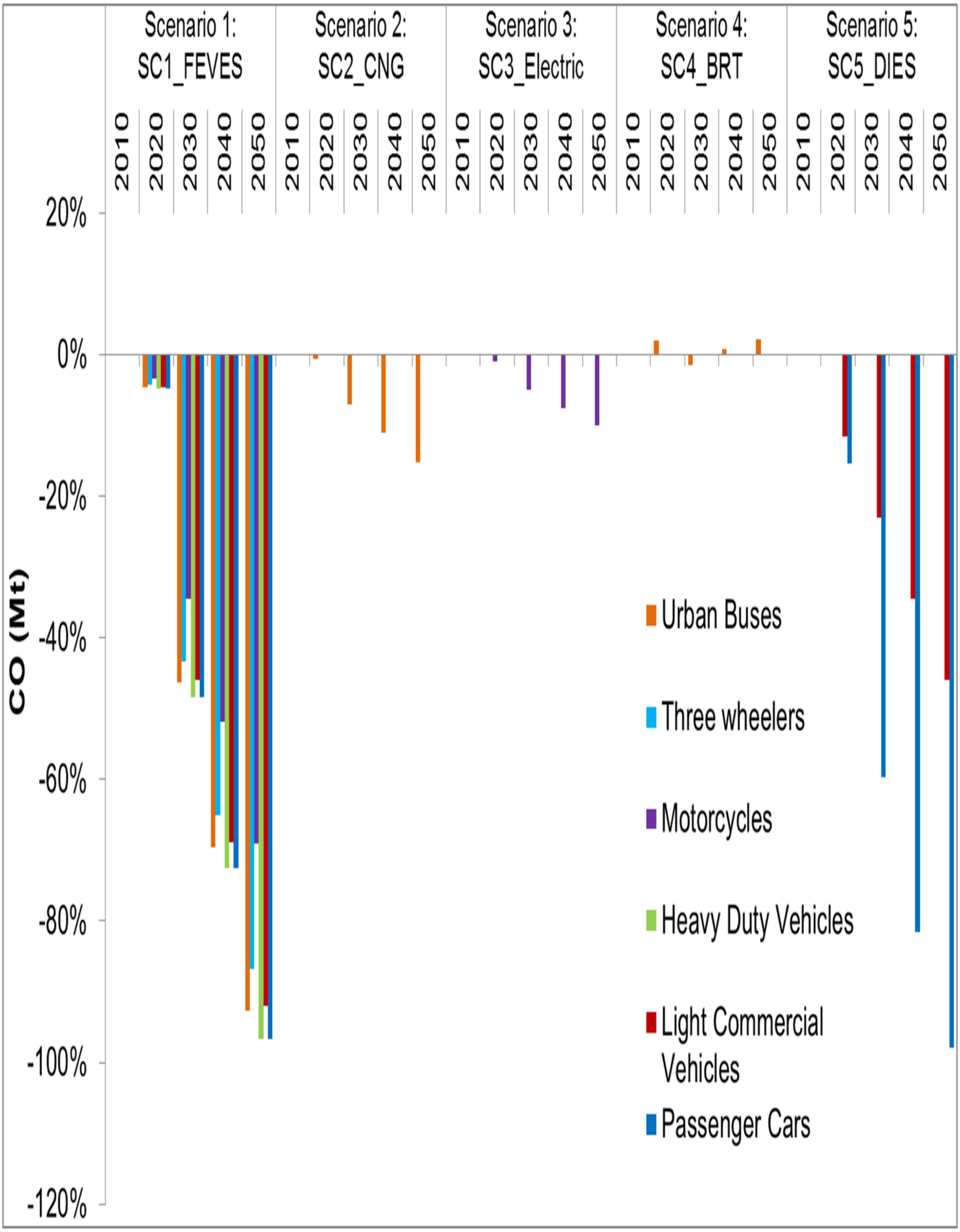

Figure S 26: CO emission reductions compared to BAU for different vehicle types

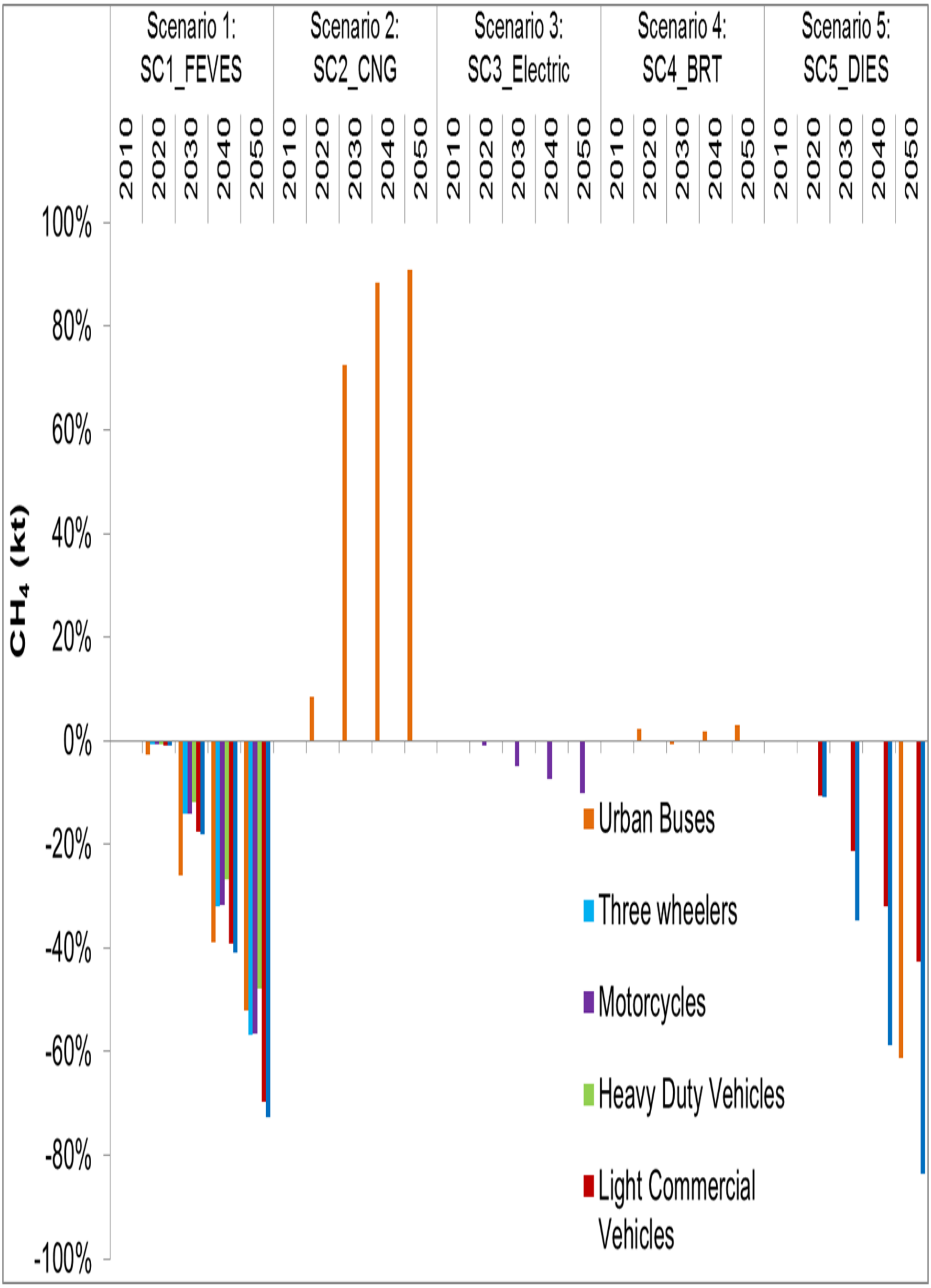

Figure S 27: CH_4 emission reductions compared to BAU for different vehicle types

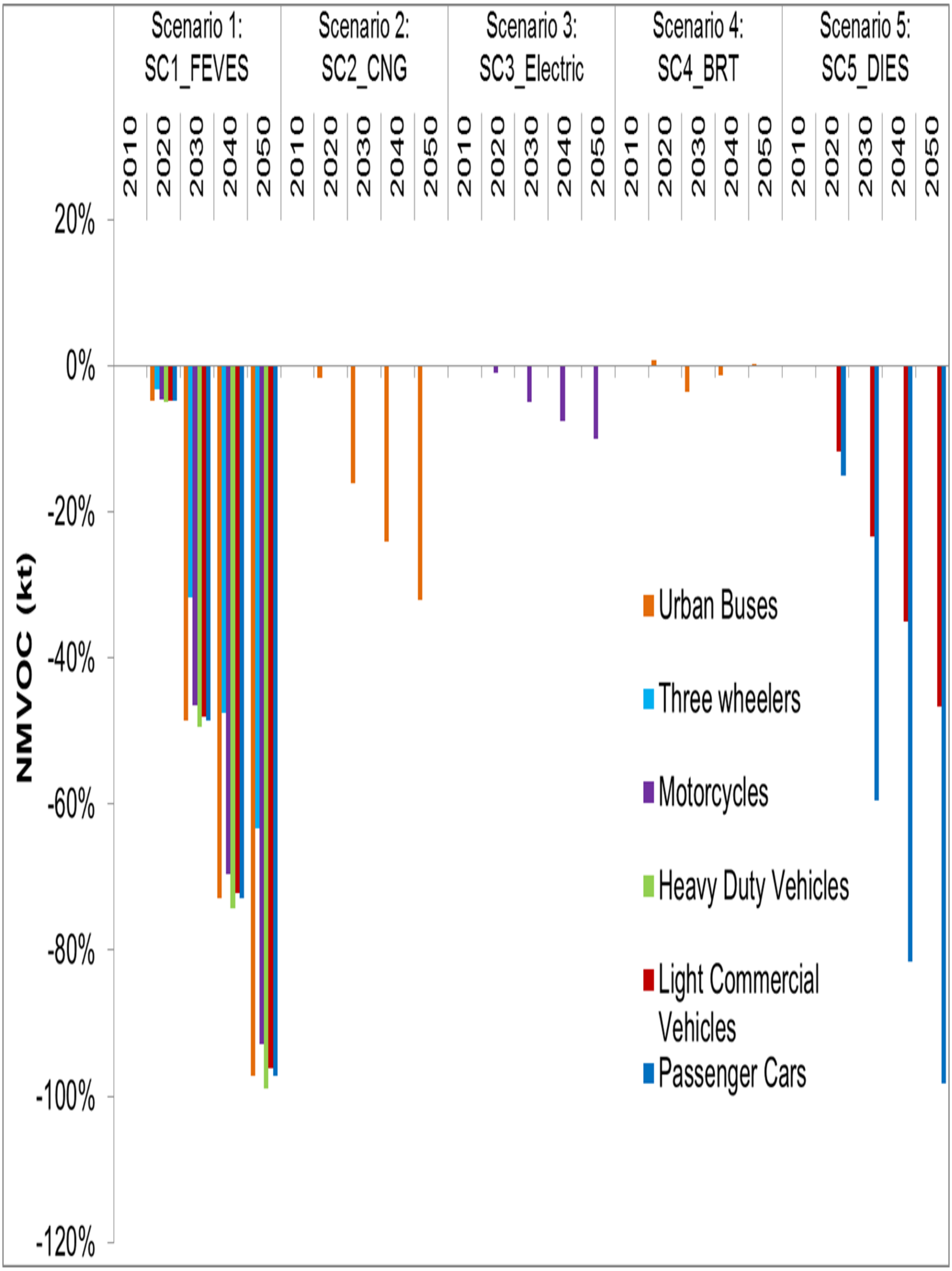

Figure S 28: NMVOC emission reductions compared to BAU for different vehicle types

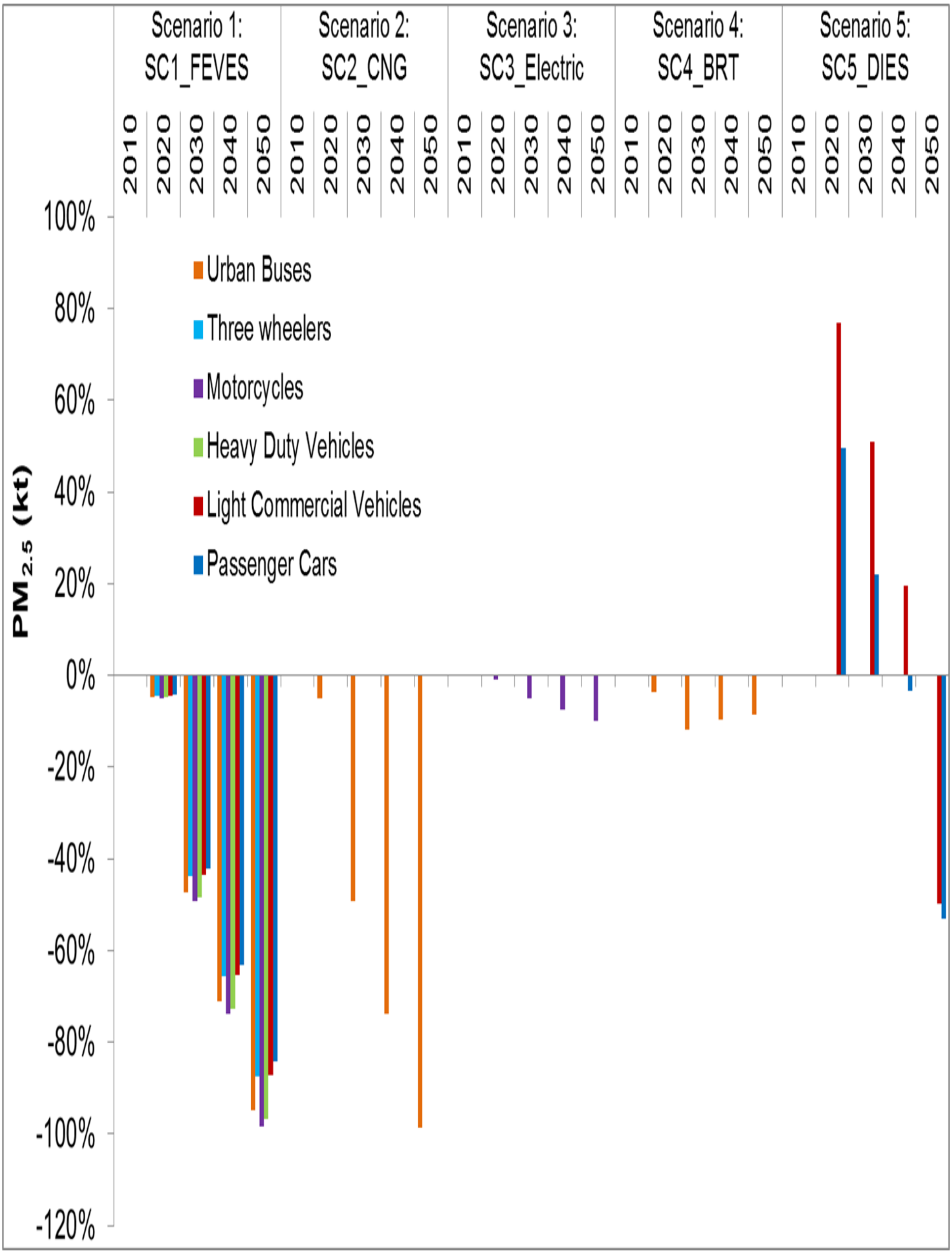

Figure S 29: $PM_{2.5}$ emission reductions compared to BAU for different vehicle types

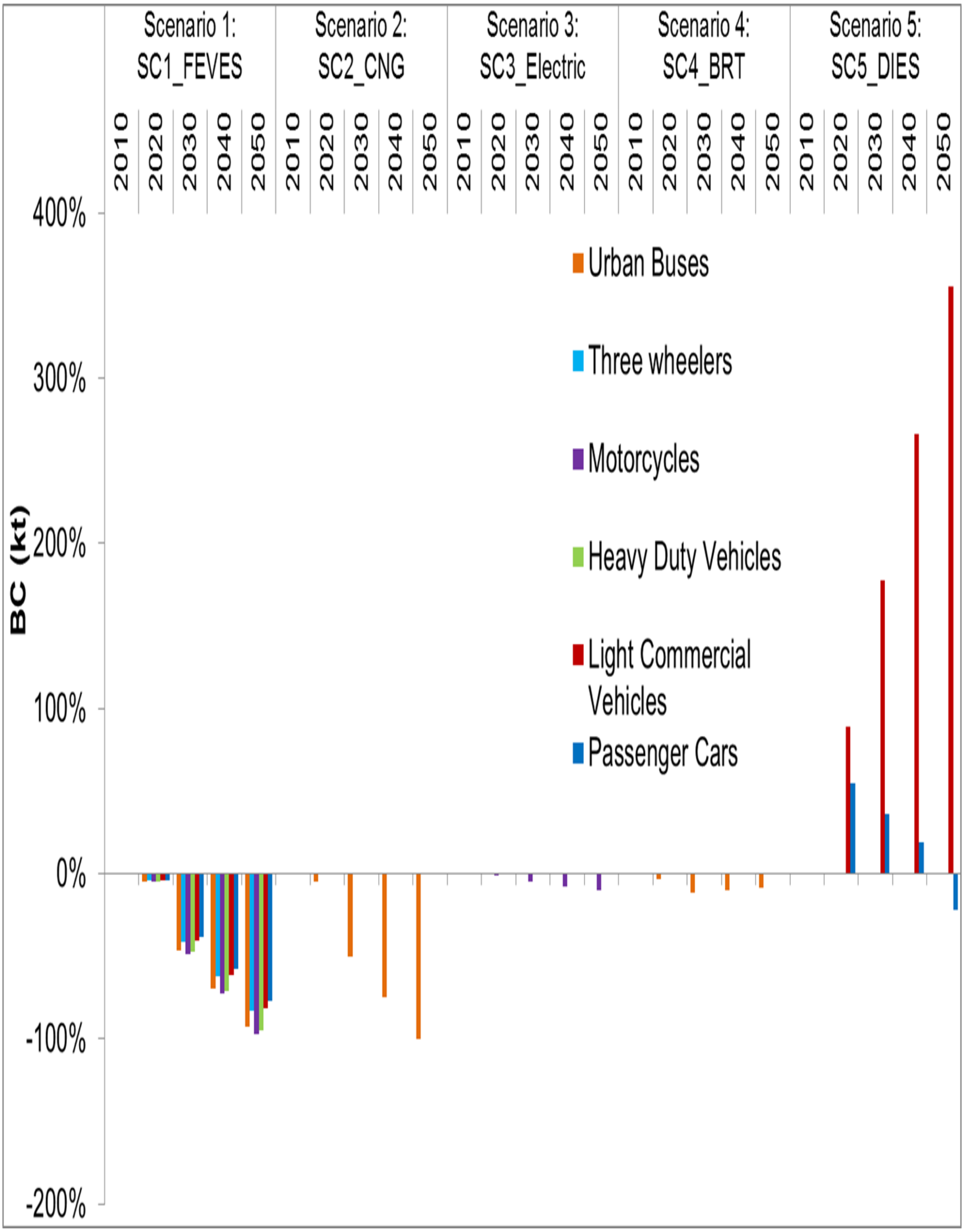

Figure S 30: BC emission reductions compared to BAU for different vehicle types

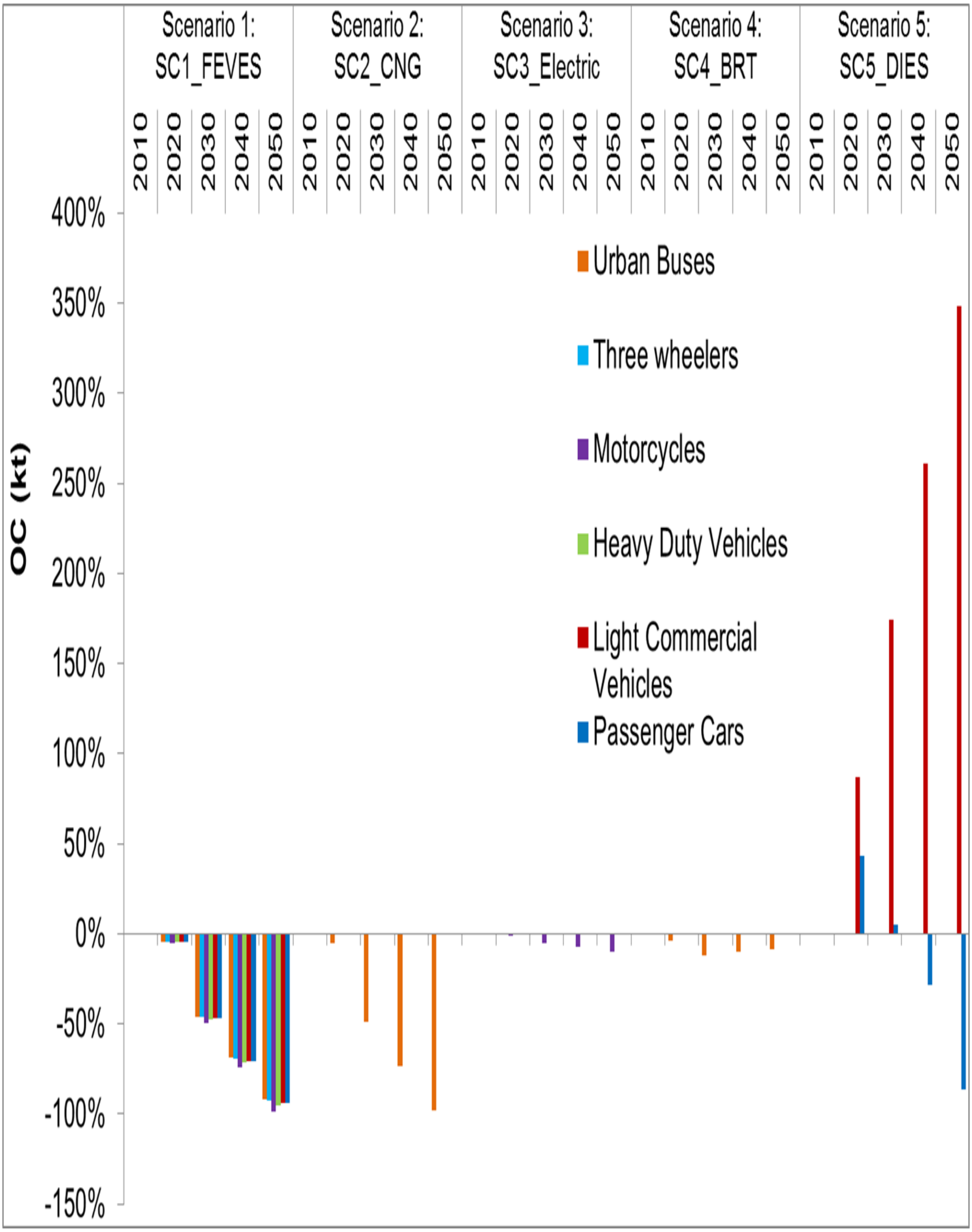

Figure S 31: OC emission reductions compared to BAU for different vehicle types

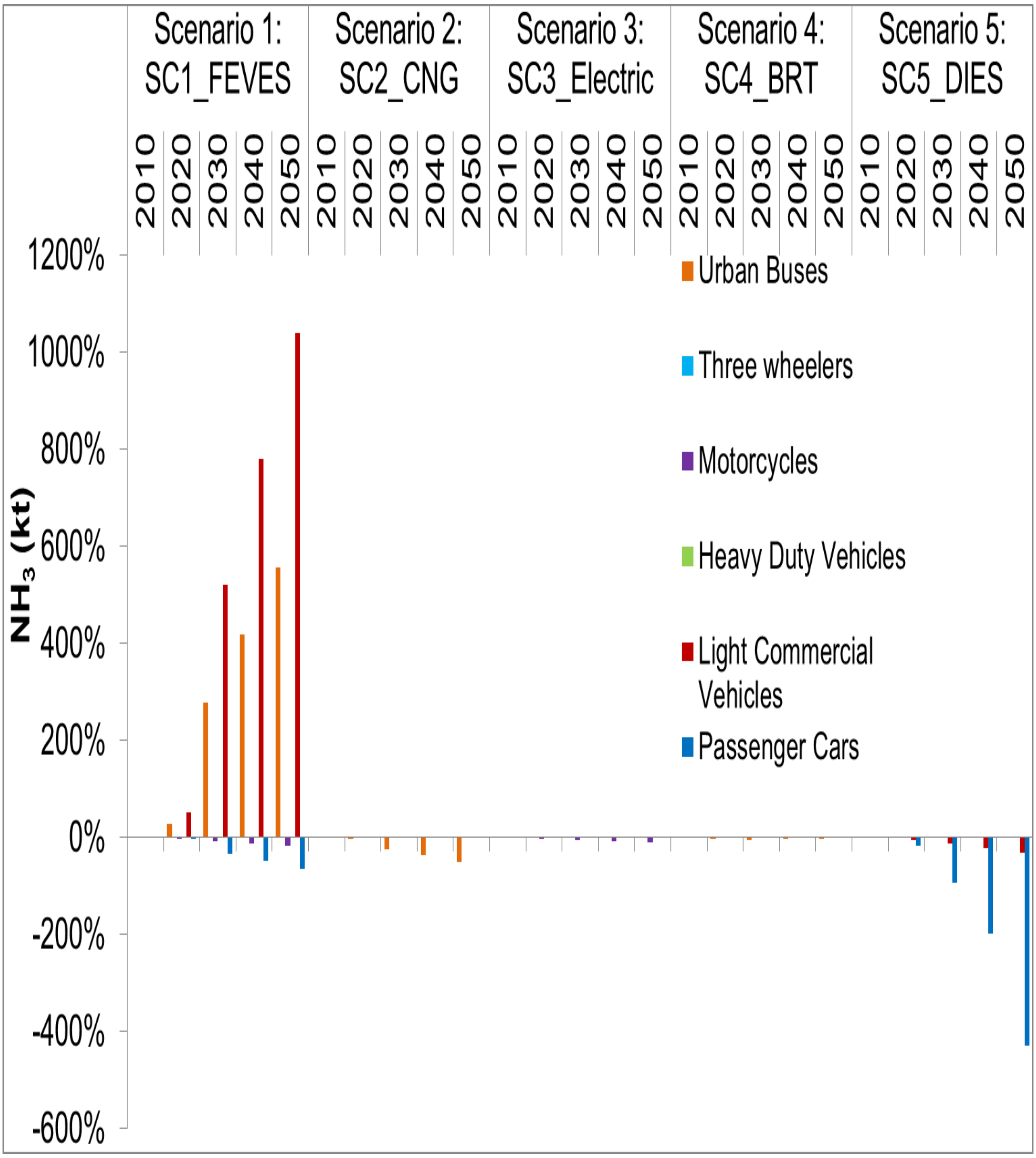

Figure S 32: NH_3 emission reductions compared to BAU for different vehicle types

CHAPTER 5

5 Synthesis

Kenya, like most of sub-Saharan African (SSA) countries, is particularly vulnerable to climate, agriculture and health impacts from air pollution concentrations of vehicle emissions (Shindell *et al.*, 2011). Road transport emissions are significant contributors to air pollution and GHGs, and their contribution is likely to increase substantially across SSA as population and income increases and as a more polluting vehicle fleet becomes part the SSA transport fleet. In a global context, SSA will bear a disproportionate burden of the effects of air pollution (Schwela, 2012), but despite this, at present there is a lack of reliable data in SSA to effectively evaluate the environmental and human health impacts of air pollution, and the potential benefits from implementing strategies to mitigate them. For example, emissions inventories, essential tools of air quality management, rely on regionally or continentally derived data in SSA. Little is known in SSA of the on-road tail-pipe emissions, activity and characteristics of the vehicle fleets, therefore compiling a detailed, accurate, transparent, verifiable and replicable national emissions inventory is often challenging. This in turn limits the assessment of the efficacy of proposed or even implemented national road transport policies aimed at mitigating the impacts of air pollution in SSA countries. Amegah et al., (2016) identified several road transport policy initiatives and the provision of adequate data for policymakers to support implementation of policies and evaluate progress as part of an integrated solution to air pollution reduction in SSA. These data needs to be provided timeously with limited resource, therefore innovative solutions that can be deliver credible local data and is replicable in several SSA countries is needed. This study set out to fill in this data gaps and provide a crucial link between micro-scale tailpipe emissions, to an urban vehicle fleet fuel economy, to a national level impact of various road transport policies on air pollution and greenhouse gases.

The aim of this thesis was therefore to design, and demonstrate a practical application of a framework that can be used to investigate road transport contributions to air pollution in

SSA countries at the individual vehicle, city, and national levels. Therefore in this thesis, road transport emissions were investigated at multiple scales. At the finest scale, PM emissions from the tailpipe of the vehicle were measured for a few vehicles using a novel multiplexed portable measurement system. At the urban scale a model for fuel economy was constructed for a fleet from data collected. Finally at the national scale, available data gathered on fuel economy, and vehicle activity and emissions were integrated to provide a country level assessment of air pollution and GHG emissions from road transport, including evaluation of transport policies to reduce air pollution and GHGs were assessed.

5.1 Developing a framework for multi-scale road transport emission analysis

The research presented in this thesis across three different scales of analysis (vehicle, city, and national-scale) can be brought together within the European Environment Agency (EEA) Drivers-Pressures-State-Impact-Responses (DPSIR) framework for transport (EEA, 1999), see Figure 5.1. In Figure 5.1, the impact of air pollution on human health and the environment is determined by air pollution concentrations, which are in turn determined by pressures such as vehicle emissions, and emissions from other sources. The extent to which a particular source sector emits pollutants or greenhouse gases is determined by a set of drivers, and efforts to abate the impacts through emission reductions require a response that changes the extent to which a driver produces the emissions profile of the transportation sector.

In this work, the proposed entry point for assessment of the extent of the impact of emissions on human health, climate and the environment, and the effectiveness of particular responses at reducing the road transport contribution to the impact is a national scale road transport emission inventory (denoted as macro-scale analysis in Figure 5.1). The rationale behind a national road transport emission inventory, specifically in Kenya, is that the national government in Kenya is best placed to implement policies that can result in changes to the vehicle fleet, and hence emissions from the road transport sector. However, as outlined, the data required to develop such an inventory is scarce in SSA countries. Hence two additional analyses, at finer scales were developed to demonstrate how they could be applied to generate data that could feed into and improve a national scale assessment of road transport emissions. Specifically, an emission inventory requires information on the activity from a particular sector, and emission factors for that activity. Therefore, the urban, meso-scale study conducted in this work was designed to improve understanding of the vehicle fleet in a large SSA city (in this case NMR). Finally, the third, finest scale study conducted in this framework assessed PM emissions from vehicles during real world driving conditions. In this thesis, these studies are presented in order of increasing scale, i.e. from micro, to meso, to macro level.

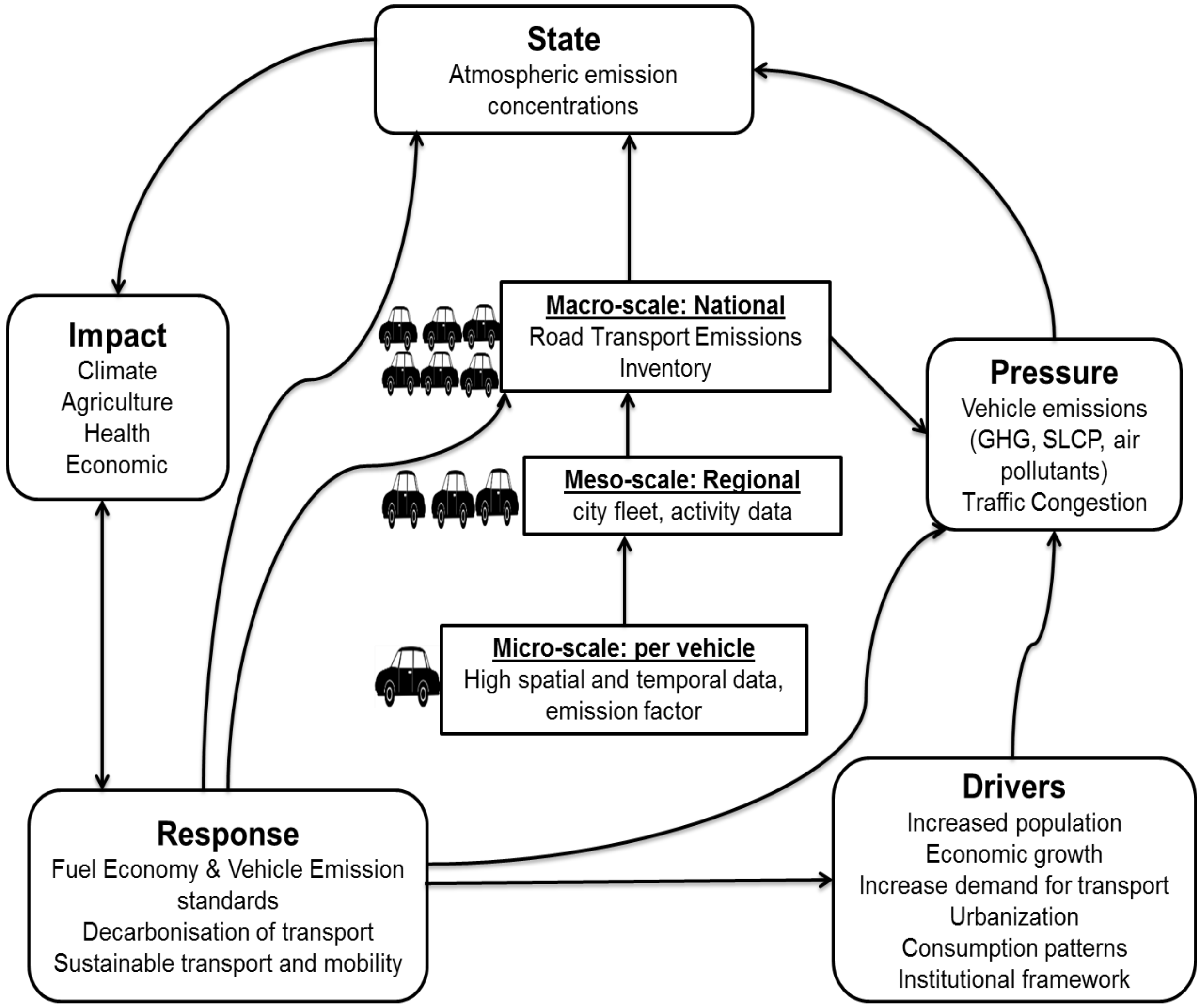

Figure 5-1: The Drivers-Pressure-State-Impact-Response (DPSIR) framework for road transport air pollution. Adapted (EEA, 1999).

Emission factors are ordinarily determined at the micro-level whereby a small representative group of cars undergo on-road emission testing in addition to the laboratory testing. In **Chapter 2**, micro-scale tail pipe emission measurements were carried out using a PM PEMS measurement system. The data obtained was at a high spatial and temporal resolution and could be used to determine changes in PM emissions under a range of driving modes. The emissions data collected from application of this methodology that used the prototype could potentially be used in the future to measure PM emission factors for fleets in SSA which have not previously been measured. In addition to the **Drivers** for increasing vehicle emissions in SSA, old vehicles, poor or absent vehicle emission regulation and enforcement, roads in bad condition and poor fuel quality means that the vehicle fleets in SSA are highly polluting and therefore their emission factors need to be measured rather than using emission factors determined for fleets in developed countries. But these present a challenge in tailpipe emission measurement in a number of ways: the initial cost of instrumentations is high therefore beyond the reach for most of SSA institutions, increasingly these instruments are made for “cleaner” vehicles in developed countries (unlike the SSA fleet), therefore, they are likely to malfunction in SSA, after-sale support is non-existent as instruments and spare parts are available outside of Africa, complex on-road testing procedures and data analysis necessitates a high level of technical competency also lacking in SSA as they is a shortage of training facilities and trained personnel.

In **Chapter 3**, at the meso-scale level, data were collected to define characteristics and vehicle activity for the urban fleet; according to different types of in-use vehicles. Whilst micro-scale predictions are suitable for evaluating driving styles, traffic design and performance and can be used to generate emission factors (Zhang, 2006), these were unavailable for Kenya. It was deemed not viable in Kenya to estimate vehicle activity at the micro-scale, but rather at a meso-scale (for an urban fleet) because on-road emission testing is expensive and time consuming especially on many different vehicles needed for an adequate sample and the different routes to test on, so as to have a representative sample for a city (Lents *et al.*, 2004; Goyns, 2008). An alternative approach is to collect data through questionnaire surveys from which estimates of the likely emission rates of a representative vehicle fleet can be made. This approach was used in this study with 826 questionnaires used to collect in-use vehicle activity data and characteristics at city scale in Kenya.

The vehicle activity and characteristics of the vehicle fleet in NMR was used in **Chapter 4** as input to compile a national transport emission inventory for Kenya. This therefore sees the compilation of emissions inventory data at the macro-scale for the transport sector. This emissions inventory would allow estimates of emissions of a number of key pollutants: SO_2, NO_X, CO_2, CO, CH_4, NMVOC, PM_{10}, $PM_{2.5}$, BC, OC and NH_3. Road transport emissions significance was put in context by compiling emissions from all other sectors in Kenya and comparing these sectors to road transport emissions. The efficacy of the current and future **response** to reduce air pollution from the road transport sector through a variety of different policies: e.g. introduction of vehicle emissions and fuel economy standards, fuel share shifts to more renewable energy sources, investment in a better public transport among other policies were assessed at various stages through various scenarios from 2010 to 2050.

5.2 Key research findings

In Chapter 2, on-road data PM measurement were conducted on light duty diesel vehicles, on a selected route using a PM PEMS prototype with three sensors operating in tandem and a measurement system to determine vehicle activity. Examples were presented of ionization, opacity and scattering sensor voltage measurements from the PM PEMS aligned with VSP for each journey of the vehicles tested, this were indicative of exhaust PM emissions. This study established that for the majority (75%) of the time, all sensors during acceleration compared to idling and acceleration driving modes had a higher sensor voltage. Therefore, it was shown VSP correlates well to sensor voltage. More insight was gained on the effect of increase of power of the vehicles tested through turbo-charging; it was shown this increased the sensor voltage. Sensor voltage was therefore sensitive engine load and to the intensity of acceleration, idle and deceleration driving modes and that the parSYNC® prototype used in the measurements was found to be fit for purpose for identifying on-road diesel vehicles with high PM emissions and possible PM pollution hot-spots in an urban area. Furthermore, VSP profile of a vehicle in a typical route in Nairobi was shown to be similar to a vehicle in a congested city with high altitude such as Bogota (Rodríguez *et al.*, 2016). A previous study noted the lack of driving cycles which account for local urban driving conditions and styles in African urban environment (Goyns, 2008), this study and Rodriguez et al., (2016) proposed vehicle emissions inventory could be improved by considering the high proportion of idling. Furthermore, mean VSP for passenger vehicles for a remote sensing survey in Europe (8.9 kW t^{-1})(Carslaw and Rhys-Tyler, 2013), was nearly 5 times more than the present study, further demonstrating the need for the differences in driving conditions urban areas in SSA. Therefore, in SSA appropriate vehicle emissions tests and instrumentation to identify high PM polluters together with relevant policy, needs to be in place to reduce emissions especially in residential areas with high idling incidences.

In Chapter 3, a questionnaire survey was developed to collect data describing vehicle activity data and characteristics. These data were analyzed and collated leading to the development of a fuel economy model for a fleet in NMR for both formal and informal vehicle fleets. Formal fleets were identified as private cars, motorcycles light and heavy duty trucks while informal fleets were identified as minibuses (*matatus)*, three-wheelers (*tuktuks*), goods vehicles (*AskforTransport*) and two-wheelers (*bodabodas*). The application of this type of questionnaire survey for data collection is necessary due to the lack of official statistics describing urban/national vehicle fleets (e.g. mileage and age of the vehicles in-use), particularly in developing countries. A key vehicle activity is fuel economy as this determines energy consumption of the transport sector and the associated GHGs emissions, globally, transport sector accounts for a nearly a quarter of fossil fuel GHG emissions (IEA, 2015).In the present study, the results show that fuel economy for *bodabodas* 4.55 ±0.38 L/100 km, *tuktuks* 8.73 ±4.68 L/100 km, passenger cars 22.77 ±3.00 L/100 km, *and matatus 33.09 ±2.49 L/100* km was 2-3 times worse when compared to fuel economy reported for Japan, Europe, India and China, from where these vehicles are imported. The vehicle fleet average ages were relatively high: *bodaboda* 2.69±0.38 years, passenger cars 11.1±0.57 years, *matatu* 8.80±1.24 years. The study also highlighted high intensity vehicle usage with an average mileage for *bodabodas* 79.7 ±4.3 km/day, *tuktuks* 114.29 ±45.6 km/day, passenger cars 61.04 ±7.18

km/day, and *matatus* 151.55 ±10.42 km/day. The high mileage and poor fuel economy results in a substantial contribution to GHGs and air pollution from the informal transport sector, but given the higher number of passengers per vehicle for these vehicles (26 ± 9 passengers) found in this study, then per person contribution is lower than private vehicles, often with an average of one passenger (ICCT, 2012). The optimal fuel economy model (GLM model) created from the present study (correlation between observed and predicted values, $r^2 = 0.60$, $P < 0.001$), identified engine size, weight of vehicle and the condition the vehicle as key variables with a significant relation to the calculated fuel economy. Therefore, in designing a questionnaire to obtain vehicle fleet characteristics and activity, these variables ought to be prioritized.

In Chapter 4, the contribution of road transport emissions to total pollution for key air pollutants and GHGs was investigated with a detailed, 'bottom up' inventory using own vehicle activity and characteristics data from the study in Chapter 3. All emissions from the other sectors were also quantified; this placed current road transport emissions in context. This found that in 2010, for the 11 air pollutants and GHGs, road transport emissions accounted for 61% NO_X, 39% $PM_{2.5}$, 20% CO_2, 19% NMVOC and 7% BC but in the BAU scenario these emissions were estimated to increase from 4-fold to nearly 31-fold by 2050. In this scenario, by 2050, motorcycles account for nearly all pollutants except NO_X, as they come to dominate the vehicle fleet. However, implementation of policies to ensure that all fleet vehicles have vehicle emissions standards equivalent to Euro IV standards and meet Japanese fuel economy standards for 2015 by 2050 in Kenya, will reduce emissions of CO_2 by 61%, BC by 93% and 65% for NO_X. In addition, we show road transport as an important sector where control of emissions can lead to large reductions in both air pollutants and GHGs. Vehicle emissions standards, fuel economy standards, fuel shift to CNG and electricity together with investment in public transport are shown to be a highly effective transport policies that support Kenya's climate change mitigation goals with a benefit of better air quality and improved health.

These studies strengthens the link between road transport emissions, tail-pipe measurements, fleet models, national inventories and relevant policy by assessing options available to policy makers and quantifying how ultimately this would lead to real-world reductions of vehicle emissions for a country such as Kenya facing air pollution challenge but with limited data.

5.3 Novelty of the research and implications

To the author's knowledge, only one real world PEMS study has been conducted in Kenya (Lents *et al.*, 2005). In this, study second-by-second tailpipe conducted in Nairobi gaseous emissions for CO, CO_2, NO_x and total hydrocarbons (THC) were measured for 113 petrol passenger vehicles for thirty minutes. Vehicle speed was estimated by an attached GPS unit and flow rates measured with a pitot flow measurement device. In data analysis, time alignment between the flow measurements, speed and emissions were further refined using VSP determined from the GPS unit. In this study there were clear trends of reduced emissions for newer cars in Nairobi, increased CO_2 emissions for larger vehicles , for CO, NO_X and THC, vehicles with the least technology (non-catalysts) were most polluting; this were the majority of the vehicle sampled vehicle fleet in Nairobi. This study is however outdated in the fast changing SSA urban environment because, vehicle fleets (age, technology, fuel share, fuel quality), vehicle types and driving patterns can change rapidly in SSA given the rapid increase in vehicle numbers. Goyns (2008) discussed the significant changes in driving conditions in South Africa in 22 years due to vehicle population growth. Lents et al., (2005) also focused on petrol light duty passenger vehicles, because a previous survey had identified 80% of Nairobi's vehicle fleet to be passenger vehicles, this has changed as motorcycles there are now more than registered cars in Kenya (KNBS, 2013b, 2014b). Furthermore, fuel quality has improved such that we do not have unleaded fuel in Kenya.

In Chapter 2, to the author's knowledge, the first real-world tailpipe measurement of PM in Kenya using a prototype PEMS was conducted for light duty diesel vehicles. The novel approach developed in this study was to employ a criterion in the methodology to select a portable, accurate, inexpensive and easy to deploy PM PEMS that would circumvent the need for expensive type-approval instrument as most SSA governments tasked with enforcement of vehicle emissions limits have limited resources and capacity. Since a prototype was deployed, data cleaning and processing framework was adopted and developed to calculate VSP from engine data (speed, position) and align it to the 3 PEMS sensor voltage (scattering, ionization and opacity) data and subsequently analyse the data. The micro-scale measurement provided high density spatial temporal pollution and activity data and developed a data quality assurance framework for the PM prototype used for the first time in a challenging environment. The environment for measurement was challenging because of the state of the typical fleet in Kenya, the traffic congestion in NMR and the state of the roads. Most roads in NMR are heavily congested (Gachanja, 2012), particularly between 07:00-10:00 and 16:00-19:00, therefore a strict protocol was applied to ensure the journey was representative and of diverse speed profile of real driving with portions of the journey including urban, peri-urban and rural driving. The road network in Kenya is under developed it is therefore in poor condition with potholes and mostly unpaved in parts (Ministry of Transport Kenya, 2011; Gachanja, 2012). In the present study, PM sensor voltage indicative of tailpipe emissions for the diesel vehicles tested was found to be highest in acceleration mode compared to idling and deceleration, these results are similar to another study conducted in China, for diesel cars light duty and heavy duty, tailpipe particle number (PN) was found to be highest in the highest acceleration (Huang *et al.*, 2013). The spatial resolution in the present study, by mapping the data (position and sensor voltage), characterizes localized pollution tailpipe hotspots in NMR roads. Insights gained from the on-road testing in NMR using the PM PEMS prototype, methodology tested for the rapid deployment and data presented could be used to supplement traditional tail-pipe measurements which are expensive and limiting especially for SSA where there is lack of region specific emission factors for fleets which are considered dissimilar to fleets in developed countries where previous tailpipe measurements have been carried out. This in turn will support the improvement of transport policy, effective reduction of on-road PM pollution and improvement of air quality for African cities.

Improving fuel economy reduces consumption of fossil fuels from the transport sector; this reduces GHGs and its impacts on the climate (Bandivadekar *et al.*, 2016; Plotkin, 2016). A previous study estimated Kenyan fuel economy to be near equivalent to European and Japanese standards but with a time lag of 8 years(ERC, 2015b). This study was possibly an under-estimate of the fuel economy of the Kenyan fleet, this is because in the absence of vehicle activity data it was assumed that the fuel economy of the Kenyan fleet was equivalent to European fleets of the same year of manufacture; in addition the study only assessed newly registered vehicles and of these only light-duty vehicles and not vehicles in circulation. The newly registered vehicles (2010-2012) were all less than 8 years old, as there is an 8 year age limit for vehicles imported into Kenya. Fuel economy deteriorates as vehicle age increases, but the studies to understand how emissions and fuel economy change with age are conducted in developed countries where they factor deterioration for vehicles under 500 000 km mileage (Boulter *et al.*, 2009; Pillot *et al.*, 2014). The typical vehicle fleets in SSA are made up of reconditioned or rebuilt vehicles whose mileage is likely to be between 800, 000 to 1, 600, 000 km therefore the declared fuel economy for developed countries will not be similar for vehicles in Kenya. **In Chapter 3**, a fuel economy model was built from questionnaire data for the in-use NMR fleet; this includes both informal and formal transport types that are prevalent in Kenya. Fuel economy was estimated directly from the questionnaire data describing vehicle activity (i.e. as a function of fuel use and vehicle mileage travelled). This estimate was then used to assess the reliability of more complex fuel economy models which aimed to account for particular aspects of vehicle characteristics and driving conditions. Two modelling approaches were used: a General Linear Model

(GLM) and an Artificial Neural Network (ANN) model. Both models were built using vehicle characteristics (age, engine size, vehicle weight, condition in which vehicle was bought, number of seats) and compared to the fuel economy calculated from vehicle activity, the results showed that the GLM model performed better than the ANN model at predicting fuel economy. In addition, the fuel economy of this fleet was compared with other fleets of developed cities.

The estimates for GHGs from the transport sector underpinning the policy to reduce 30% of GHG from energy sector identified a lack of official statistics for fuel economy and in-use vehicle activity in Kenya (Cameron *et al.*, 2012) . This study provides a methodology that allows the estimation of fuel economy for regions where data are lacking and specifically to allow the collection of data describing age and mileage of the in-use vehicle fleet; key variables that would reduce the uncertainty in estimating emissions from the transport sector to aid in both air quality management and to target GHG emission reduction more effectively. Furthermore, this study has been able to establish a fuel economy baseline for the NMR fleet to be 2 to 3 times poorer than developed countries, which can be measured against when fuel economy policies are implemented.

Air pollution from the transport sector is often under estimated in global inventories but it is increasing in Africa mainly in urban areas where the vehicle fleet size is also increasing (Assamoi and Liousse, 2010; Liousse *et al.*, 2014). This is because there is often a lack of vehicle activity data, fuel share knowledge, region specific emission factors and poor registration of vehicles from which these factors could be estimated for the fleet; particularly for certain transport types such as motorcycles and shared taxis. In Kenya, global inventories have estimated emissions from several sectors using top-down methods with international data (GBD, 2015; Marais and Wiedinmyer, 2016; Susan C Anenberg *et al.*, 2017). These assessments have explored emissions impact on human health in Kenya and found that 6 508 premature deaths per year are caused by ambient PM pollution (GBD, 2015). This was estimated to cost Kenya $2 244 million per year

(Roy, 2016). A national inventory for GHGs that focused on the transport sector found 37% of CO_2 equivalent GHG emissions could be reduced from the BAU scenario with the implementation of various low-carbon options for transport (Cameron *et al.*, 2012). These studies used top-down data fuel consumption data and lacked local activity data; vehicle mileage, fuel and technology split disaggregated by vehicle types. In Chapter 4, a detailed “bottom-up” transport sector emission inventory was compiled as well as an emission inventory for other sectors using top-down methods for the following pollutant species: SO_2, NO_X, CO_2, CO, CH_4, NMVOC, $PM_{2.5}$, PM_{10}, BC, OC and NH_3. Future trends of emissions were analysed for Kenya’s road transport sector to demonstrate the effectiveness of possible reduction measures. These focussed on policies that would: i) see the implementation of stricter vehicle emission and fuel economy standards; ii) cleaner fuels and; iii) investment in better public transport in urban areas. There would be multiple benefits for human health, agriculture and climate (from the reduction in emissions of particular pollutant species (i.e. PM and ozone pre-cursors) , these have been extensively explored in other studies (Shindell *et al.*, 2011; GBD, 2015; Forouzanfar *et al.*, 2016; Lacey *et al.*, 2017) ; quantifying the impacts of air pollution concentration is beyond the scope of the present study and to be explored in future work.

5.4 Policy implications

The thesis analysis of the different scales air pollution from the micro, meso and macro level similarly brings about policy implications at these same levels. In chapter 2, the PEMS prototype deployed if developed further could bring about access to a more simple, light, cost-effective and robust solution to measure real world exhaust emissions for a vehicle pollute that is highly polluting. The high temporal and spatial data would be useful to key stakeholders in two ways: generation of PM emissions factors and identifying ‘hotspots’ of pollution. Accurate PM emissions factors are important for improved emission inventories and identifying hotspot, this is increasingly used for prediction and modeling purposes as well as planning to reduce the contribution of transport emissions to air pollution. The cost-effective portable emission measurement system could also be used by governments for a more accurate enforcement and compliance measurements in the inspection and maintenance programs.

In chapter 3, at the meso-scale, estimating the fuel economy of vehicles in-use in Africa is a challenge as the vehicle activity and characteristics data is often not recorded or available. The development of a methodology for estimating urban fleet fuel economy for a country with limited data and resources bridges the gap identified. The fuel economy baseline values for Nairobi, could aid in the development of a clear-cut fuel economy policy to reduce GHGs and air pollution, underpinned by accurate data and a model that could support prediction and thus planning for the growing vehicle fleet in a city like Nairobi.

In Chapter 4, at the macro-level, estimating GHGs and air pollution from all sectors using local and international data supports the progress of nationally determined contributions plans for Kenya as well as air quality management, both of which are under development. It also accurately portrays the contribution of the transport sector for each pollutant, this supports formulation of national policy to mitigate the impacts of pollution to climate, health and agriculture.

5.5 Limitations and future work

The limitations of each study in this research have been described in in detail in each chapter. **In Chapter 2**, deployment of a PEMS prototype for the first time in Nairobi to measure real world tailpipe PM emissions brought about challenges compared to deploying and testing in a developed country; environmental or practical challenges, and sample vehicle representativeness. Environment challenges included the conditions of the roads in Nairobi, a lot of roads were unpaved and or with potholes, this caused a particular sensitivity to the instrument which was identified as voltage ‘jumps’ when the vehicle was momentarily on the unpaved or porthole part of the road. In addition, traffic congestion was also of particular concern, if the tests were conducted when traffic was gridlocked , this would extend the test time and the instruments charge (laptop, phone) would dissipate to a point where results were no longer uploaded, this happened for some test runs which were no longer viable. There were also frequent instrument malfunction, made all the more challenging by a lack of technical support in the immediate vicinity (manufacturers were based in North America). Because vehicle emission standards and I/M programs are not enforced in Kenya, it was challenging to characterize vehicles technology (emission reduction devices) using the year of manufacture and reliable fuel quality, apart from issue of fuel adulteration which is rampant in Kenya, fuel quality standards because have also changed in the last 5 years. Therefore, the experimental procedure and the data analysis from this work, was designed to overcome this challenges, in addition to ensuring a cost effective way to undertake in future a comprehensive analysis of a larger set of vehicles to develop PM emission factors in a SSA urban setting. The study did not lead to the development of emission factors; therefore this scale this did not feed into other scales. Future work would be to repeat the real-world tailpipe measurement using the prototype and a reference instrument for a bigger sample size, more routes and vehicle categories to determine PM emission factors for a Kenyan fleet.

There are numerous challenges arising from firstly, using questionnaires as a survey instrument in transport with personal interviews, they are costly sometimes limiting sample size, time consuming, interactions bring about a question of neutrality and distortions may occur (Richardson *et al.*, 1995). Survey instruments have been used in SSA cities extensively and recommendations were previously made to address challenges; survey preparedness (inform relevant authorities of survey beforehand and obtain necessary permits), pilot tests and pre-testing of the survey, selecting and training interviewers, use pre-existing data to bolster the depth of the survey and determine sample size (Behrens *et al.*, 2006). In Chapter 3, a quantitative questionnaire vehicle fleet survey was developed to overcome these challenges and collect data describing vehicle characteristics and activity, these data were then used to develop a fuel economy model for a NMR vehicle fleet. However, there were other unforeseen limitations, firstly, the sample size was deemed adequate for the NMR vehicle population, but overall sample size per vehicle category was not adequate for example for heavy duty commercial vehicles, mainly because these types of vehicles not circulating in the city roads. Secondly, there was missing data in the questionnaire especially in the cases where the driver of the vehicle was not the owner of the vehicle. In this cases a statistical method, multiple imputations was used to deal with the missing data, this method to author's knowledge had not been used in transport survey. Thirdly, inaccurate data, vehicle sales website and manufactures website were used to verify vehicle weight and engine size given the manufacturers name, brand or make of vehicle, year of manufacture and other characteristics obtained from the questionnaire information. Finally, there was collinearity of the variables in determining the significance of the relation between calculated fuel economy and the predicted fuel economy from vehicle characteristics such as engine size, weight, odometer reading, age of vehicle, number of seats. To resolve the effect of collinearity, different variables were alternatively suppressed and the fuel economy model was re-assessed. In the end, it was determined for this course of action to be a success a bigger sample size was required, which reduced because of the missing data. Therefore future work would be one that expanded the sample size to ensure more representative fleet, to include heavy duty vehicles and counter the missing data increase the sample size. A new survey should also be undertaken at a national scale rather than an urban scale and replicated in other SSA countries.

Good practice of compiling emission inventories is one where uncertainties are reduced as far as it is practicable so as to neither have over nor under estimates of emissions and GHGs (Penman *et al.*, 2006). In chapter 4, firstly, in estimating Kenya's emissions and GHGs uncertainties for input data were estimated for emission factors, vehicle mileage (VKT) and fuel economy. The combined uncertainty for these input data for the vehicle emissions inventory was found to range from 70% to 86% for different pollutants per vehicle category. Even though the fuel economy and mileage was estimated with own data (from Chapter 3),   with uncertainty ranging from 5% to 54%, a larger uncertainty, 70%, was assumed for the emission factors. The uncertainty for emission factors was derived from Tier 1 upper bound estimate in uncertainty assessment of EMEP/EEA methodology (Ntziachristos *et al.*, 2013; Kouridis *et al.*, 2017). The emission factors used in the inventory were derived for European fleets and driving cycle, this is a limitation that was mitigated in using these emission factors for the Kenyan fleet by assuming the least technology for the Kenyan fleet. Furthermore, the activity data for fuel economy and mileage used was based on a previous study conducted in NMR, which was assumed to be representative of the whole country; this assumption was made in the absence of any other activity data. Therefore future work would be to determine real world local emission factors for all pollutants for all sectors and collect activity data for the whole country.

The findings for this thesis even with the given limitations and challenges, make a strong case for the research to continue to refine the grasp of the distintive air pollution challenges SSA faces and identify opportunities for SSA countries to adopt technologies and develop expertize in the transport sector to the particular needs and priorities of these countries.

References

3DATX (2015) *Parsync user guide manual*. Available at: http://www.3datx.com/product/parsync/ (Accessed: 1 May 2015).

Abel, K. *et al.* (2001) 'Quantifying uncertainties in practice.', in Ondingo, R. (ed.) *Good practice guidance and Uncertainty Management in National Greenhouse Gas*, pp. 247–259. Available at: http://www.ipcc-nggip.iges.or.jp/public/gp/english/.

Aduagba, O. N., Amine, J. D. and Oseni, M. I. (2013) 'Investigating Emission Values of a Passenger Vehicle in the Idle Mode and Comparison with Regulated Values', *American journal of engineering research (AJER)*, 2(3), pp. 13–19. Available at: http://www.ajer.org/papers/v2(3)/C0231319.pdf.

Aggarwal, P. and Jain, S. (2014) 'Energy demand and CO2 emissions from urban on-road transport in Delhi: current and future projections under various policy measures', *Journal of Cleaner Production*, 128, pp. 48–61. doi: 10.1016/j.jclepro.2014.12.012.

Agyemang-Bonsu, K. W., Dontwi, I. K., Tutu-Benefoh, D., Bentil, D. E., Boateng, O. G., Asuobonteng, K. and Agyemang, W. (2010) 'Traffic-data driven modelling of vehicular emissions using COPERT III in Ghana : A case study of Kumasi', *American Journal of Scientific and Industrial Research*, 134350, pp. 32–40.

Akinola, M., Lekonpane, M. and Dada, E. (2017) 'Air Quality Management in Botswana', *Clean Air Journal*, 27(1). Available at: http://www.cleanairjournal.org.za/download/volume27_no1_2017_oe03.pdf.

Alessandrini, A., Filippi, F. and Ortenzi, F. (2012) 'Consumption calculation of vehicles using OBD data', *2012 International Emission Inventory Conference 'Emission Inventories - Meeting the Challenges Posed by Emerging Global, National, Regional and Local Air Quality Issues'*, pp. 1–21.

Alice, M. (2015) *Fitting a neural network in R; neuralnet package*, *Datascienceplus*. Available at: http://datascienceplus.com/fitting-neural-network-in-r/ (Accessed: 13 June 2016).

Aligula, E. M., Abiero-gariy, Z., Mutua, J., Owegi, F., Osengo, C. and Olela, R. (2005) *Urban Public Transport Patterns in Kenya : A Case Study of Nairobi City Survey Report*. Nairobi, Kenya.

Allen, H. (2013) 'Africa's first full rapid bus system: The Rea Vaya bus system in Johannesburg, Republic of South Africa', *Case study prepared for the Global Report of Human Settlements*. Available at: http://unhabitat.org/wp-content/uploads/2013/06/GRHS.2013.Case_.Study_.Johannesburg.South_.Africa.pdf.

Amegah, A. K. and Agyei-Mensah, S. (2016) 'Urban air pollution in Sub-Saharan Africa: Time for action', *Environmental Pollution*, pp. 1–6. doi: 10.1016/j.envpol.2016.09.042.

Anderson, A. (2013) *Sasol launches lowest sulphur content diesel in South Africa | Energy*, *BDlive*. Available at: http://www.bdlive.co.za/business/energy/2013/11/21/sasol-launches-lowest-sulphur-content-diesel-in-south-africa (Accessed: 19 November 2014).

Anenberg, S. C. *et al.* (2012) 'Global air quality and health co-benefits of mitigating near-term climate change through methane and black carbon emission controls.', *Environmental health perspectives*, 120(6), pp. 831–9. doi: 10.1289/ehp.1104301.

Anenberg, S. C. *et al.* (2017) 'Impacts and mitigation of excess diesel-related NOx emissions in 11 major vehicle markets', *Nature*, (x). doi: 10.1038/nature22086.

Anenberg, S. C., Henze, D. K., Lacey, F., Irfan, A., Kinney, P., Kleiman, G. and Pillarisetti, A. (2017) 'Air pollution-related health and climate benefits of clean cookstove programs in Mozambique', *Environmental Research Letters*, 12(2), p. 25006. doi: 10.1088/1748-9326/aa5557.

Anyon P, Brown S, Pattison D, Beville-Anderson J, Walls G and Mowle M (2000) *In-Service Emissions Performance - Phase II Vehicle Testing*. Available at: http://www.nepc.gov.au/system/files/resources/45fee0f3-1266-a944-91d7-3b98439de8f8/files/dve-prepwk-project2-2.pdf.

ARAI (2008) *Emission Factor development for Indian Vehicles as a part of Ambient Air Quality Monitoring and Emission Source Apportionment Studies*. PUNE. doi: Project Rep No.: AFL/2006-07/IOCL/Emission Factor Project/Final Rep.

Arlot, S. and Celisse, A. (2010) 'A survey of cross-validation procedures for model selection', *Statistics Surveys*, 4, pp. 40–79. doi: 10.1214/09-SS054.

Assamoi, E.-M. and Liousse, C. (2010) 'A new inventory for two-wheel vehicle emissions in West Africa for 2002', *Atmospheric Environment*. Elsevier Ltd, 44(32), pp. 3985–3996. doi: 10.1016/j.atmosenv.2010.06.048.

Azur, M. J., Stuart, E. A., Frangakis, C. and Leaf, P. J. (2011) 'Multiple imputation by chained equations: What is it and how does it work?', *International Journal of Methods in Psychiatric Research*, 20(1), pp. 40–49. doi: 10.1002/mpr.329.

Baek, S. H. and Jang, J. W. (2015) 'Implementation of integrated OBD-II connector with external network', *Information Systems*. Elsevier, 50, pp. 69–75. doi: 10.1016/j.is.2014.06.011.

Bakker, S., Contreras, K. D., Kappiantari, M., Tuan, N. A., Guillen, M. D., Gunthawong, G., Zuidgeest, M., Liefferink, D. and Maarseveen, M. Van (2017) 'Low-Carbon Transport Policy in Four ASEAN Countries : Developments in Indonesia , the Philippines , Thailand and Vietnam', *Sustainability*, 8, pp. 1–17. doi: 10.3390/su9071217.

Bandivadekar, A. *et al.* (2016) *Fuel Economy State of the World 2016*. Available at: http://www.globalfueleconomy.org/media/203446/gfei-state-of-the-world-report-2016.pdf.

BBC (2015) *Weather in Kenya*. Available at: http://www.bbc.co.uk/weather/184745 (Accessed: 20 July 2015).

Be Foward Co (2017) *Japanese Used Cars*. Available at: http://www.beforward.jp/ (Accessed: 24 April 2017).

Behrens, R., Diaz-Olvera, L., Plat, D. and Pochet, P. (2006) 'Collection of passenger travel data in Sub-Saharan African cities: Towards improving survey instruments and procedures', *Transport Policy*, 13(1), pp. 85–96. doi: 10.1016/j.tranpol.2005.09.003.

Behrens, R., McCormick, D., Orero, R. and Ommeh, M. (2017) 'Improving paratransit service: Lessons from inter-city matatu cooperatives in Kenya', *Transport Policy*. Elsevier, 53(September 2016), pp. 79–88. doi: 10.1016/j.tranpol.2016.09.003.

Biering, K., Hjollund, N. H. and Frydenberg, M. (2015) 'Using multiple imputation to deal with missing data and attrition in longitudinal studies with repeated measures of patient-reported outcomes.', *Clinical epidemiology*. Dove Press, 7, pp. 91–106. doi: 10.2147/CLEP.S72247.

Bishop, G. A., Stedman, D. H. and Ashbaugh, L. (1996) 'Motor Vehicle Emissions

Variability', *Journal of the Air & Waste Management Association*, 2247(46:7), p. 667–675,. doi: 10.1080/10473289.1996.10467501 To.

Bond, T. C., Streets, D. G., Yarber, K. F., Nelson, S. M., Woo, J.-H. and Klimont, Z. (2004) 'A technology-based global inventory of black and organic carbon emissions from combustion', *Journal of Geophysical Research*, 109(D14), p. D14203. doi: 10.1029/2003JD003697.

Boroujeni, B. Y. and Christopher Frey, H. (2014) 'Road grade quantification based on global positioning system data obtained from real-world vehicle fuel use and emissions measurements', *Atmospheric Environment*, 85, pp. 179–186. doi: 10.1016/j.atmosenv.2013.12.025.

Boroujeni, B. Y., Frey, H. C. and Sandhu, G. S. (2013) 'Road Grade Measurement Using In-Vehicle, Stand-Alone GPS with Barometric Altimeter', *Journal of Transportation Engineering*, 139(6), pp. 605–611. doi: 10.1061/(ASCE)TE.1943-5436.0000545.

Boulter, P. G., Barlow, T. J. and Mccrae, I. S. (2009) *Exhaust mission factors for road vehicles in the United Kingdom*. Available at: https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/4249/report-3.pdf.

Burton, A., Billingham, L. J. and Bryan, S. (2007) 'Cost-effectiveness in clinical trials: using multiple imputation to deal with incomplete cost data', *Clinical Trials*, 4(2), pp. 154–161. doi: 10.1177/1740774507076914.

Cameron, L., Wurtenberger, L. and Stiebert, S. (2012) *Kenya's Climate Change Action Plan: Mitigation Chapter 7: Transportation*. Available at: http://www.kccap.info/index.php?option=com_phocadownload&view=category&id=36.

Cames, M. and Helmers, E. (2013) 'Critical evaluation of the European diesel car boom - global comparison, environmental effects and various national strategies', *Environmental Sciences Europe*, 25(1), p. 15. doi: 10.1186/2190-4715-25-15.

Cappiello, A., Chabini, I., Nam, E. ., Lue, A. and Zeid, A. (2002) 'A Statistical Model of Vehicle Emissions and Fuel Consumption', *… . The IEEE 5th …*, (September), pp. 801–809. Available at: http://ieeexplore.ieee.org/xpls/abs_all.jsp?arnumber=1041322.

Carslaw, D. (2015) 'The openair manual open-source tools for analysing air pollution data', *King's College London*, p. 287.

Carslaw, D. C., Beevers, S. D., Tate, J. E., Westmoreland, E. J. and Williams, M. L. (2011) 'Recent evidence concerning higher NO\n x emissions from passenger cars and light duty vehicles', *Atmospheric Environment*, 45(39), pp. 7053–7063. doi: 10.1016/j.atmosenv.2011.09.063.

Carslaw, D. C. and Rhys-Tyler, G. (2013) 'New insights from comprehensive on-road measurements of NOx, NO2 and NH3 from vehicle emission remote sensing in London, UK', *Atmospheric Environment*, 81, pp. 339–347. doi: 10.1016/j.atmosenv.2013.09.026.

Carslaw, D. C. and Ropkins, K. (2012) 'Openair - An r package for air quality data analysis', *Environmental Modelling and Software*, 27–28, pp. 52–61. doi: 10.1016/j.envsoft.2011.09.008.

Carslaw, D. C., Williams, M. L., Tate, J. E. and Beevers, S. D. (2013) 'The importance of high vehicle power for passenger car emissions', *Atmospheric Environment*, 68, pp. 8–16. doi: 10.1016/j.atmosenv.2012.11.033.

Carter, T. R. *et al.* (2001) 'Developing and applying scenarios', in Gupta, S. and Hulme, M. (eds) *Climate change 2001. Impacts, adaptation, and vulnerability. Contribution of the Working Group II to the Third Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge, UK, pp. 145–190. Available at: https://pdfs.semanticscholar.org/ec80/08634fd376647920633849c462da31874132.pdf.

Cervero, R. and Golub, A. (2007) 'Informal transport: A global perspective', *Transport Policy*, 14(6), pp. 445–457. doi: 10.1016/j.tranpol.2007.04.011.

Chambliss, S., Miller, J., Façanha, C., Minjares, R. and Blumberg, K. (2013) *The impact of stringent fuel and vehicle standards on premature mortality and emissions*. Available at: http://theicct.org/sites/default/files/publications/ICCT_HealthClimateRoadmap_2013_revised.pdf (Accessed: 16 February 2014).

Cheki Inc. (2017) *New and Used Cars For Sale In Kenya*. Available at: https://www.cheki.co.ke/ (Accessed: 24 April 2017).

Chiang, H.-L., Tsai, J.-H., Yao, Y.-C. and Ho, W.-Y. (2008) *Deterioration of gasoline vehicle emissions and effectiveness of tune-up for high-polluted vehicles*, *Transportation Research Part D: Transport and Environment*. doi: 10.1016/j.trd.2007.07.004.

Choudhary, A. and Gokhale, S. (2016) 'Urban real-world driving traffic emissions during interruption and congestion', *Transportation Research Part D: Transport and Environment*, 43, pp. 59–70. doi: 10.1016/j.trd.2015.12.006.

City of Capetown (2010) *Air Quality Management by-law, 2010*.

Clark, L. P., Millet, D. B. and Marshall, J. D. (2017) 'Changes in Transportation-Related Air Pollution Exposures by Race-Ethnicity and Socioeconomic Status : Outdoor Nitrogen Dioxide in the United States in 2000 and 2010', *Environmental health perspectives*, 125(9), pp. 1–10. doi: 10.1289/EHP959.

Dargay, J. and Gately, D. (1999) 'Income's effect on car and vehicle ownership, worldwide: 1960–2015', *Transportation Research Part A: Policy and Practice*, 33(2), pp. 101–138. doi: 10.1016/S0965-8564(98)00026-3.

Dargay, J., Gately, D. and Sommer, M. (2007) 'Vehicle Ownership and Income Growth, World wide: 1960-2030', *The Energy Journal*, 28(4), pp. 1–32. doi: 10.5547/ISSN0195-6574-EJ-Vol28-No4-7.

Degraeuwe, B. and Weiss, M. (2016) 'Does the New European Driving Cycle (NEDC) really fail to capture the NOX emissions of diesel cars in Europe?', *Environmental Pollution*. Elsevier Ltd, pp. 1–8. doi: 10.1016/j.envpol.2016.12.050.

Delphi (2017) *Worldwide emission standards Passenger cars and light duty*. Available at: https://www.delphi.com/docs/default-source/worldwide-emissions-standards/delphi-worldwide-emissions-standards-passenger-cars-light-duty-2016-7.pdf.

Department of Environmental Affairs (2009) *National Environmental Management: Air Quality Act, 2004 (Act No.39 of 2004) National ambient air quality standards*. South Africa. Available at: https://www.gov.za/sites/default/files/32816_1210.pdf.

Department of Environmental Affairs (2012) *National Ambient Air Quality Standards for Particulate Matter with an Aerodynamic Diameter of less than 2.5 micrometres (PM2.5)*, *Government Gazette,*. South Africa. Available at: https://www.environment.gov.za/sites/default/files/gazetted_notices/nemaqa_ambientair_ quality_g35463gen486.pdf.

Van Dessel, G. (2013) *How to determine population and survey sample size?* Available at: https://www.checkmarket.com/2013/02/how-to-estimate-your-population-and-survey-sample-size/ (Accessed: 27 August 2014).

Van Dingenen, R., Dentener, F. J., Raes, F., Krol, M. C., Emberson, L. and Cofala, J. (2009) 'The global impact of ozone on agricultural crop yields under current and future air quality legislation', *Atmospheric Environment*. Elsevier Ltd, 43(3), pp. 604–618. doi: 10.1016/j.atmosenv.2008.10.033.

Dionisio, K. L., Arku, R. E., Hughes, A. F., Vallarino, J., Carmichael, H., Spengler, J. D., Agyei-Mensah, S. and Ezzati, M. (2010) 'Air pollution in Accra neighborhoods: spatial, socioeconomic, and temporal patterns.', *Environ. Sci. Technol*. American Chemical Society, 44(7), pp. 2270–6. doi: 10.1021/es903276s.

Doumbia, E. H. T. *et al.* (2012) 'Real time black carbon measurements in West and Central Africa urban sites', *Atmospheric Environment*. Elsevier Ltd, 54, pp. 529–537. doi: 10.1016/j.atmosenv.2012.02.005.

Droppa, D. (2012) *SA to get cleaner 'Euro 5' fuel*, *IOL*. Available at: http://www.iol.co.za/motoring/industry-news/sa-to-get-cleaner-euro-5-fuel-1.1314000#.VGyUl8lAj_8 (Accessed: 19 November 2014).

EAC (2011a) *East African Standard: Automotive gas oil (automotive diesel)-Specification*, *EAC*. Available at: http://www.eac-quality.net/fileadmin/eac_quality/user_documents/3_pdf/EAS_177-2011__Automotive_diesel_-_Specification.pdf (Accessed: 18 November 2014).

EAC (2011b) *East African Standard: Automotive gasoline (Premium motor spirit)-specification*, *EAC*. EAC. Available at: http://www.eac-quality.net/fileadmin/eac_quality/user_documents/3_pdf/EAS_158-2011__Automotive_gasoline_-_Specification.pdf (Accessed: 18 November 2014).

EEA (1999) *Towards a transport and environment reporting mechanism (TERM) for the EU Part 1 : TERM concept and process*, *European Environment Agency*. Copenhagen.

EMEP/EEA (2013) 'EMEP/EEA air pollutant emission inventory guidebook 2013', in. doi: 10.2800/92722.

EPA (2006) '13.2.2 Unpaved Roads', in *Compilation of Air Pollutant Emission Factors, Volume I: Stationary Point and Area Sources, AP-42*. 5th edn. United States Environmental Protection Agency, pp. 1–20. Available at: https://www3.epa.gov/ttnchie1/ap42/ch13/final/c13s0202.pdf.

EPA (2014) *Light-Duty Automotive Technology, Carbon Dioxide Emissions, and Fuel Economy Trends: 1975 Through 2014*.

ERC (2015a) *Fuel prices at the pump*. Available at: http://www.erc.go.ke/index.php?option=com_content&view=article&id=162&Itemid=666 (Accessed: 3 August 2015).

ERC (2015b) *Report on global fuel economy initiative study in Kenya (GFEI)*. Available at: http://www.erc.go.ke/index.php?option=com_content&view=article&id=224&Itemid=721.

European Commission (2016) *Commission Regulation (EU) 2016/427 of 10 March 2016* *amending Regulation (EC) No 692/2008 as regards emissions from light passenger and commercial vehicles (Euro 6) (Text with EEA relevance)*, *Official Journal of the European Union*. Available at: http://eur-lex.europa.eu/legal-content/EN/ALL/?uri=CELEX:32016R0427.

Faiz, A., Weaver, C. and Walsh, M. P. (1996) *Air pollution from motor vehicles Standards and Technologies for Controlling Emissions*. Washington, DC. Available at: http://www.un.org/esa/gite/iandm/faizpaper.pdf.

FAO (2017) *FAOSTAT:Kenya- Animal numbers;Area harvested;crop processed; crop production;fertilizer consumptions and production;forestry production, savannah burning*. Available at: http://www.fao.org/faostat/en/#data/QD (Accessed: 1 March 2017).

FIA (2017) *Can we prevent another dieselgate?* Available at: http://www.fiafoundation.org/media/418769/dieselgate-lr-spreads.pdf.

Fincham, J. E. (2008) ‘Response rates and responsiveness for surveys, standards, and the Journal.’, *American journal of pharmaceutical education*. American Association of Colleges of Pharmacy, 72(2), p. 43. Available at: http://www.ncbi.nlm.nih.gov/pubmed/18483608 (Accessed: 27 August 2014).

Forbes, P. and Labuschagne, K. (2004) ‘Development of South African vehicle emission factors’, *National Association for Clean Air Conference (NACA 2009)*. Available at: http://researchspace.csir.co.za/dspace/bitstream/10204/3876/1/ForbesP_2009.pdf.

Forouzanfar, M. H. *et al.* (2016) ‘Global, regional, and national comparative risk assessment of 79 behavioural, environmental and occupational, and metabolic risks or clusters of risks, 1990-2015: a systematic analysis for the Global Burden of Disease Study 2015’, *The Lancet*, 388(10053), pp. 1659–1724. doi: 10.1016/S0140-6736(16)31679-8.

Franco, V., Kousoulidou, M., Muntean, M., Ntziachristos, L., Hausberger, S. and Dilara, P. (2013) ‘Road vehicle emission factors development: A review’, *Atmospheric Environment*, pp. 84–97. doi: 10.1016/j.atmosenv.2013.01.006.

Franco, V., Posada Sánchez, F., German, J. and Mock, P. (2014) *Real-world exhaust emissions from modern diesel cars. A meta-analysis of PEMS emissions data from EU (Euro 6) and US (Tier 2 Bin 5/ULEV II) diesel passenger cars. Part 1: Aggregated results*. Available at: http://www.theicct.org/sites/default/files/publications/ICCT_PEMS-study_diesel-cars_20141010.pdf.

Frey, H. C. and Rouphail, N. M. (2008) ‘Fuel Use and Emissions Comparisons for Alternative Routes, Time of Day, Road Grade, and Vehicles Based on In-Use Measurements’, pp. 2483–2489. doi: 10.1021/es702493v.

Frey, H. C., Unal, A., Rouphail, N. M. and Colyar, J. D. (2003) ‘On-Road Measurement of Vehicle Tailpipe Emissions Using a Portable Instrument’, *Journal of the Air & Waste Management Association*, 53(8), pp. 992–1002. doi: 10.1080/10473289.2003.10466245.

Fritsch, S., Guenther, F., Suling, M. and Mueller, M. S. (2016) ‘Training of Neural Networks’, pp. 1–13. Available at: https://cran.r-project.org/web/packages/neuralnet/neuralnet.pdf.

Fu, J. (2013) ‘The Role of Electric Two-Wheelers in Sustainable Urban Transport in China: Market analysis, trends, issues, policy options’, *Sustainable Development, United Nations*, pp. 1–17. Available at: https://sustainabledevelopment.un.org/content/documents/3792fu2.pdf.

Fukubayashi, Y., Daito, Y. and Kimura, M. (2016) 'Locally Available Geotextile for Maintaining Unpaved Roads in Developing Countries to Enhance Community Resilience', *Procedia Engineering*, 145, pp. 348–355. doi: 10.1016/j.proeng.2016.04.087.

Gachanja, J. N. (2012) *Evaluating the Impact of Road Traffic Congestion Mitigation Measures in Nairobi Metropolitan Region*. Nairobi, Kenya. Available at: http://kippra.or.ke/index.php?option=com_docman&task=doc_view&gid=264&Itemid=.

Gagolewski, M. and Tartanus, B. (2016) 'R package stringi: Character string processing facilities.' doi: 10.5281/zenodo.32557.

Gaita, S. M., Boman, J., Gatari, M. J., Pettersson, J. B. C. and Janhäll, S. (2014) 'Source apportionment and seasonal variation of PM2.5 in a Sub-Sahara African city: Nairobi, Kenya', *Atmospheric Chemistry and Physics Discussions*, 14, pp. 9565–9601. doi: 10.5194/acpd-14-9565-2014.

Garcia, V. (2014) *Evaluation and improvement of road vehicle pollutant emission factors based on instantaneous emissions data processing*.

Gatari, M. J., Gachanja, A., Graeff, J. and Sclar, E. (2013) 'Black carbon in Archived samples of 2009 air quality study in Nairobi , Kenya Experimental Results and Discussions', (2008), p. 2009.

Gatari, M., Wagner, A. and Boman, J. (2005) 'Elemental composition of tropospheric aerosols in Hanoi, Vietnam and Nairobi, Kenya.', *Science of The Total Environment*, 341(1–3), pp. 241–9. doi: 10.1016/j.scitotenv.2004.09.031.

GBD (2015) *Global burden of Disease Study 2015-Results by risk factor-country level (online data base-Viz Hub-GBD Compare)*. Seattle. Available at: https://vizhub.healthdata.org/gbd-compare/.

Giechaskiel, B., Maricq, M., Ntziachristos, L., Dardiotis, C., Wang, X., Axmann, H., Bergmann, A. and Schindler, W. (2014) 'Review of motor vehicle particulate emissions sampling and measurement: From smoke and filter mass to particle number', *Journal of Aerosol Science*, 67, pp. 48–86. doi: 10.1016/j.jaerosci.2013.09.003.

Gillies, J. A., Etyemezian, V., Kuhns, H., Nikolic, D. and Gillette, D. A. (2005) 'Effect of vehicle characteristics on unpaved road dust emissions', *Atmospheric Environment*, 39(13), pp. 2341–2347. doi: 10.1016/j.atmosenv.2004.05.064.

Gitari, W. (2000) *Determination of the levels of heavy metals in suspended particulate matter (SPM) in Kibera (Nairobi)*. University of Nairobi.

Goel, R. and Guttikunda, S. K. (2015) 'Evolution of on-road vehicle exhaust emissions in Delhi', *Atmospheric Environment*. Elsevier Ltd, 105, pp. 78–90. doi: 10.1016/j.atmosenv.2015.01.045.

Goel, R., Guttikunda, S. K., Mohan, D. and Tiwari, G. (2014) 'Benchmarking vehicle and passenger travel characteristics in Delhi for on-road emissions analysis', *Travel Behaviour and Society*. Hong Kong Society for Transportation Studies. doi: 10.1016/j.tbs.2014.10.001.

Goel, R., Mohan, D., Guttikunda, S. K. and Tiwari, G. (2015) 'Assessment of motor vehicle use characteristics in three Indian cities', *Transportation Research Part D: Transport and Environment*. doi: 10.1016/j.trd.2015.05.006.

Goh, A. T. C. (1995) 'Back-propagation neural networks for modeling complex systems', *Artificial Intelligence in Engineering*. Elsevier Science Limited, 9(94), pp. 143–151.

Government of Kenya (2012) *National Climate Change Action Plan: Mitigation*. Available at: http://www.kccap.info/index.php?option=com_phocadownload&view=category&id=36.

Government of Kenya (2013) *National Climate Change Action Plan 2013 -2017*.

Government of Rwanda (2014) *Prime ministers instructions No. 005/03 of 27/12/2013 Preventing air pollution caused by vehicular emissions and macheines using petroleum products in Rwanda*. Rwanda. Available at: http://www.minirena.gov.rw/fileadmin/Environment_Subsector/Laws__Policies_and_Programmes/Laws/Laws.pdf.

Goyns, P. H. (2008) *Modelling real-world driving , fuel consumption and emissions of passenger vehicles : a case study in Johannesburg*. University of Johannesburg.

Graeff, J. (2008) ‘The Organization and Future of the Matatu Industry in Nairobi , Kenya’, p. 12. Available at: http://www.vref.se/download/18.53e8780912f2dbbe3a580002295/Organization+and+Future+of+the+Matatu+Industry.pdf.

GRASS Development Team (2015) ‘Geographic Resources Analysis Support System (GRASS) Software’. Open Source Geospatial Foundation. Available at: https://grass.osgeo.org/home/about-us/.

Grolemund, G. and Wickham, H. (2011) ‘Dates and Time Made Easy with lubridate’, *Journal of Statistical Software*, 40(3), pp. 1–25. Available at: http://www.jstatsoft.org/v40/i03.

Guo, H., Zhang, Q., Shi, Y. and Wang, D. (2007) ‘Evaluation of the International Vehicle Emission (IVE) model with on-road remote sensing measurements’, *Journal of Environmental Sciences*, 19(7), pp. 818–826. doi: 10.1016/S1001-0742(07)60137-5.

Gyimesi, K., Vincent, C. and Lamba, N. (2011) *Frustration rising: IBM 2011 commuter pain survey*. Available at: http://www.ibm.com/smarterplanet/us/en/traffic_congestion/ideas/index.html (Accessed: 26 February 2014).

Hao, H., Wang, S., Liu, Z. and Zhao, F. (2016) ‘The impact of stepped fuel economy targets on automaker’s light-weighting strategy: The China case’, *Energy*, 94, pp. 755–765. doi: 10.1016/j.energy.2015.11.051.

Haq, G. and Weiss, M. (2016) ‘CO2 labelling of passenger cars in Europe: Status, challenges, and future prospects’, *Energy Policy*, 95, pp. 324–335. doi: 10.1016/j.enpol.2016.04.043.

Heaps, C. . (2016) ‘Long-range Energy Alternatives Planning (LEAP) system’. Somerville, MA, USA: Stockholm Environment Institute, pp. 1–81. Available at: www.energycommunity.org (Accessed: 27 June 2017).

Helmers, E. (2016) *Does the European diesel car boom mitigate global warming ?* Available at: http://green-budget.eu/wp-content/uploads/2016-02-17_Helmers_European-diesel-car-bias-makes-climate-worse1.pdf.

Hill, N., Finnegan, S., Norris, J., Brannigan, C., Wyann, D., Baker, H. and Skinner, I. (2011) *Reduction and Testing of Greenhouse Gas (GHG) Emissions from Heavy Duty Vehicles – Lot 1: Strategy*, *AEA/Ricardo*.

Ho, B. Q. and Clappier, A. (2011) 'Road traffic emission inventory for air quality modelling and to evaluate the abatement strategies: A case of Ho Chi Minh City, Vietnam', *Atmospheric Environment*. Elsevier Ltd, 45(21), pp. 3584–3593. doi: 10.1016/j.atmosenv.2011.03.073.

Holmes, T. (2013) 'Nigeria seeks SA's vehicle expertise', *Mail and Guardian*, 2 August. Available at: http://mg.co.za/article/2013-08-02-00-nigeria-seeks-sas-vehicle-expertise.

Honaker, J., King, G. and Blackwell, M. (2011) 'AMELIA II : A Program for Missing Data', *Journal Of Statistical Software*, 45(7), pp. 1–54. doi: 10.1.1.149.9611.

Horton, N. J. and Lipsitz, S. R. (2001) 'Multiple Imputation in Practice : Comparison of Software Packages for Regression Models with Missing Variables Author (s): Nicholas J . Horton and Stuart R . Lipsitz Published by : Taylor & Francis , Ltd . on behalf of the American Statistical Associati', *The American Statistician*, 55(3), pp. 244–254.

Hu, J., Wu, Y., Wang, Z., Li, Z., Zhou, Y., Wang, H., Bao, X. and Hao, J. (2012) 'Real-world fuel efficiency and exhaust emissions of light-duty diesel vehicles and their correlation with road conditions', *Journal of Environmental Sciences*, 24(5), pp. 865–874. doi: 10.1016/S1001-0742(11)60878-4.

Huang, C., Lou, D., Hu, Z., Feng, Q., Chen, Y., Chen, C., Tan, P. and Yao, D. (2013) 'A PEMS study of the emissions of gaseous pollutants and ultrafine particles from gasoline- and diesel-fueled vehicles', *Atmospheric Environment*. Elsevier Ltd, 77, pp. 703–710. doi: 10.1016/j.atmosenv.2013.05.059.

Huo, H., He, K., Wang, M. and Yao, Z. (2012) 'Vehicle technologies, fuel-economy policies, and fuel-consumption rates of Chinese vehicles', *Energy Policy*, 43, pp. 30–36. doi: 10.1016/j.enpol.2011.09.064.

Huo, H., Yao, Z., He, K. and Yu, X. (2011) 'Fuel consumption rates of passenger cars in China: Labels versus real-world', *Energy Policy*, 39(11), pp. 7130–7135. doi: 10.1016/j.enpol.2011.08.031.

Ibarra-espinosa, S., Ynoue, R., Sullivan, S. O., Pebesma, E., Andrade, M. D. F. and Osses, M. (2017) 'VEIN v0 . 2 . 2 : an R package for bottom-up Vehicular Emissions Inventories', *Geoscientific Model Development Discussions*, (September), pp. 1–29. Available at: https://www.geosci-model-dev-discuss.net/gmd-2017-193/gmd-2017-193.pdf.

ICCT (2012) *Cost and benefits of clean technologies for bus rapid transit (BRT): Summary of results for Nairobi*.

IEA (2011) *International comparison of light-duty vehicle fuel economy and related characteristics*. Available at: http://www.globalfueleconomy.org/Documents/Publications/wp5_iea_fuel_Economy_report.pdf.

IEA (2012a) 'Technology Roadmap Fuel Economy of Road Vehicles'. doi: 10.1007/SpringerReference_7300.

IEA (2012b) *World Energy Balances of OECD and non-OECD Countries 1971-2011*. Paris: International Energy Agency (IEA). Available at: https://www.iea.org/statistics/relateddatabases/worldenergystatisticsandbalances/.

IEA (2015) *Excerpt from CO2 Emissions from fuel combustion (2015 Edition)*. Available at: www.iea.org/t&c/ (Accessed: 23 May 2016).

IEA (2017) *International comparison of light-duty vehicle fuel economy and related characteristics*. Available at: http://www.globalfueleconomy.org/Documents/Publications/wp5_iea_fuel_Economy_report.pdf.

IIASA (2016) *ECLIPSE Project (ECLIPSE(Evaluating the Climate and Air Quality Impacts of Short-Lived Pollutants Project no.282688*. Available at: http://www.iiasa.ac.at/web/home/research/researchPrograms/air/ECLIPSEv5.html (Accessed: 18 August 2017).

IPCC (2006) 'Cover - IPCC Guidelines for National Greenhouse Gas Inventories, Volume 2, Energy', *2006 IPCC Guidelines for National Greenhouse Gas Inventories*, 2, p. 5. Available at: http://www.ipcc-nggip.iges.or.jp/public/2006gl/vol2.html.

Isuzu Kenya (2014) *ISUZU-KENYA BUS SPECIFICATIONS*. Available at: http://www.isuzutrucks.co.ke/33-seater-bus#overview (Accessed: 11 December 2014).

JAMA (2016) *2016 REPORT ON ENVIRONMENTAL PROTECTION EFFORTS Promoting Sustainability in Road Transport in Japan*.

Japan Car Direct (2015) *The Toyota Hiace Van for East Africa - Japan Car Direct*. Available at: http://www.japancardirect.com/buy-second-hand-cars-from-japan-domestic-market-from-japan-car-direct/the-toyota-hiace-van-for-east-africa (Accessed: 17 June 2015).

Ježek, I., Drinovec, L., Ferrero, L., Carriero, M. and Močnik, G. (2015) 'Determination of car on-road black carbon and particle number emission factors and comparison between mobile and stationary measurements', *Atmospheric Measurement Techniques*, 8(1), pp. 43–55. doi: 10.5194/amt-8-43-2015.

JICA (2006) *The Study on Master Plan for Urban Transport in the Nairobi Metropolitan Area in The Republic of Kenya*. Nairobi, Kenya. Available at: http://libopac.jica.go.jp/images/report/P0000168672.html.

JICA (2014) *The Project on Integrated Urban Development Master Plan for the City of Nairobi in the Republic of Kenya Final Report*. Nairobi, Kenya. Available at: http://citymasterplan.nairobi.go.ke/index.php/downloads/cat_view/4-niuplan-studies/23-draft-masterplan.

Jiménez-Palacios, J. L. (1999) *Understanding and Quantifying Motor Vehicle Emissions with Vehicle Specific Power and TILDAS Remote Sensing*. Massachusetts Institute of Technology.

Kahle, D. and Wickham, H. (2013) 'ggmap : Spatial Visualization with ggplot2', *The R Journal*, 5(1), pp. 144–161. doi: 10.1023/A:1009843930701.

KEBS (2007) *Motor gasolines - Specification (Withdrawn and rep/KS 2060:2007 - Full Catalogue Listing*, *Kenya Gazette notice No. 9223 of 2007-09-21*. Available at: http://onlinecatalogue.kebs.org/webquery.dll?v1=pbMarc&v4=0&v5=5A&v8=475953&v9=0&v10=N&v13=4A&v20=4&v23=0&v25=KS and 2060 and 2007&v27=5399&v29=5A&v35=%7B]0[%7D%7B]0[%7D%7B]0[%7D%7B]0[%7D&v40=475951&v46=475953 (Accessed: 18 November 2014).

KEBS (2010) *Diesel fuels - Specification - Part 1: Automotive /KS 1309-1:2010 - Full Catalogue Listing*, *Legal Notice No. 176 of 1997*. Available at: http://onlinecatalogue.kebs.org/webquery.dll?v1=pbMarc&v4=0&v5=5A&v8=475987&v9=0&v10=N&v13=4A&v20=4&v23=0&v25=KS and 1309 and

1&v27=1891&v29=5A&v35=%7B]0[%7D%7B]0[%7D%7B]0[%7D%7B]0[%7D&v40=475985&v46=475987 (Accessed: 18 November 2014).

KEBS (2014) *KS 1515:2000 Code of practice for inspection of road vehicles*. Kenya: Kenya Bureau of Standards. Available at: http://www.kebs.org/?opt=qai&view=motor-vehicle-inspection (Accessed: 16 March 2015).

Kenward, M. G. G. and Carpenter, J. (2007) 'Multiple imputation: current perspectives.', *Statistical methods in medical research*, 16(3), pp. 199–218. doi: 10.1177/0962280206075304.

Khan, M. Y., Johnson, K. C., Durbin, T. D., Jung, H., Cocker, D. R., Bishnu, D. and Giannelli, R. (2012) 'Characterization of PM-PEMS for in-use measurements conducted during validation testing for the PM-PEMS measurement allowance program', *Atmospheric Environment*. Elsevier Ltd, 55, pp. 311–318. doi: 10.1016/j.atmosenv.2012.03.004.

Kholod, N., Evans, M., Gusev, E., Yu, S., Malyshev, V., Tretyakova, S. and Barinov, A. (2016) 'A methodology for calculating transport emissions in cities with limited traffic data: Case study of diesel particulates and black carbon emissions in Murmansk', *Science of The Total Environment*, 547, pp. 305–313. doi: 10.1016/j.scitotenv.2015.12.151.

Kinney, P. L. *et al.* (2011) 'Traffic Impacts on PM(2.5) Air Quality in Nairobi, Kenya.', *Environmental science & policy*, 14(4), pp. 369–378. doi: 10.1016/j.envsci.2011.02.005.

Kishimoto, P. N., Karplus, V. J., Zhong, M., Saikawa, E., Zhang, X. and Zhang, X. (2017) 'The impact of coordinated policies on air pollution emissions from road transportation in China', *Transportation Research Part D: Transport and Environment*. Elsevier Ltd, 54, pp. 30–49. doi: 10.1016/j.trd.2017.02.012.

Klimont, Z., Kupiainen, K., Heyes, C., Purohit, P., Cofala, J., Rafaj, P., Borken-Kleefeld, J. and Schöpp, W. (2017) 'Global anthropogenic emissions of particulate matter including black carbon', *Atmospheric Chemistry and Physics*, (October), pp. 1–72. doi: 10.5194/acp-17-8681-2017.

KNBS (2013a) 'Nairobi County'. Kenya National Bureau of Statistics. Available at: http://www.knbs.or.ke/index.php?option=com_phocadownload&view=category&id=115:county-report&Itemid=599&limitstart=20.

KNBS (2013b) *Transport -Registered Vehicles*, *Kenya National Bureau of Statistics*. Available at: http://www.knbs.or.ke/index.php?option=com_phocadownload&view=category&id=91:transport&Itemid=1163 (Accessed: 18 March 2014).

KNBS (2014a) *Information on the REVISED NATIONAL ACCOUNTS Kenya National Bureau of Statistics*. Available at: http://knbs.or.ke/index.php?option=com_phocadownload&view=category&download=604:information-on-the-revised-national-accounts&id=17:gross-domestic-product&Itemid=597.

KNBS (2014b) *Kenya National Bureau of Statistics Kenya Facts and Figures , 2014*. Available at: http://www.knbs.or.ke/index.php?option=com_phocadownload&view=category&id=20&Itemid=1107.

Kneen, M. A. and Annegarn, H. J. (1996) 'Algorithm for fitting XRF, SEM and PIXE X-ray spectra backgrounds', *Nuclear Instruments and Methods in Physics Research, Section B: Beam Interactions with Materials and Atoms*, 109–110, pp. 209–213. doi: 10.1016/0168-583X(95)00908-6.

Kolawole, G. (2010) 'An Evaluation of the Impact of Bus Rapid Transit in Urban Intra-city Passenger movement in Lagos State', *12th World Conference for Transportation Research*, pp. 1–20. Available at: http://www.wctrs.leeds.ac.uk/wp/wp-content/uploads/abstracts/lisbon/general/01011.pdf.

Kouridis, C. *et al.* (2014) 'Road Transport', in *EMEP/EEA air pollutant emission inventory guidebook - 2016*.

Kouridis, C. *et al.* (2017) '1.A.3.b.I-IV Road Transport 2016', in *EMEP/EEA air pollutant emission inventory guidebook - 2016*. Available at: https://www.eea.europa.eu/publications/emep-eea-guidebook-2016.

Kouridis, C., Gkatzoflias, D., Kioutsioukis, I. and Ntziachristos, L. (2009) *Uncertainty estimates and guidance for road transport emission calculations*. doi: 10.2788/78236.

Kousoulidou, M., Fontaras, G., Ntziachristos, L., Bonnel, P., Samaras, Z. and Dilara, P. (2013) 'Use of portable emissions measurement system (PEMS) for the development and validation of passenger car emission factors', *Atmospheric Environment*. Elsevier Ltd, 64(x), pp. 329–338. doi: 10.1016/j.atmosenv.2012.09.062.

KRA (2016) *KRA Motorcycle Import Duty Calculator 2016*, *Kenya Revenue Authority*. Available at: http://calculator.co.ke/kra-motorcycle-import-duty-calculator (Accessed: 9 August 2016).

Kumar, A. (2011) *Understanding the emerging role of motorcycles in African cities: A political economy perspective*, *Sub-Saharan Africa Transport Policy Program (SSATP) discussion paper*. Washington, DC. Available at: http://documents.worldbank.org/curated/en/391141468007199012/Understanding-the-emerging-role-of-motorcycles-in-African-cities-a-political-economy-perspective.

Kumar, A. and Barrett, F. (2008) 'Stuck in traffic: Urban transport in Africa', *AICD Background Paper*. Available at: http://siteresources.worldbank.org/EXTAFRSUBSAHTRA/Resources/Stuck-in-Traffic.pdf (Accessed: 22 May 2014).

Kuranc, A. (2015) 'Exhaust emission test performance with the use of the signal from air flow meter', *Maintenance and Reliability*, 17(1), pp. 129–134. Available at: http://www.ein.org.pl/sites/default/files/2015-01-17.pdf.

Lacey, F. and Henze, D. (2015) 'Global climate impacts of country-level primary carbonaceous aerosol from solid-fuel cookstove emissions', *Environmental Research Letters*. IOP Publishing, 10(11), p. 114003. doi: 10.1088/1748-9326/10/11/114003.

Lacey, G. F., Marais, E. A., Henze, D. K., Lee, C. J., van Donkelaar, A., Martin, R. V., Hannigan, M. P. and Wiedinmyer, C. (2017) 'Improving present day and future estimates of anthropogenic sectoral emissions and the resulting air quality impacts in Africa', in *Faraday Discussions*, pp. 1–16. doi: 10.1039/C7FD00011A.

Law, K., Jackson, M. and Chan, M. (2011) *European Union Greenhouse Gas Reduction Potential for Heavy-Duty Vehicles*. Available at: http://ec.europa.eu/clima/policies/transport/vehicles/heavy/docs/icct_ghg_reduction_potential_en.pdf.

Lee, M., Park, Y., Jung, K. and Yoo, J. (2011) 'Estimation of Fuel Consumption using In-Vehicle Parameters.', *International Journal of U-& E-Service, Science …*, 4(4), pp. 37–46. Available at: http://scholar.google.com/scholar?hl=en&btnG=Search&q=intitle:Estimation+of+Fuel+Consumption+using+In-Vehicle+Parameters#0 (Accessed: 5 June 2014).

Lents, J., Davis, N., Nikkila, N., Osses, M., Martinez, H. and Ehsani, S. (2005) 'Measurement of in-use passenger vehicle emissions in three urban areas of developing nations'. Available at: http://www.issrc.org/ive/downloads/reports/VER3Cities.pdf (Accessed: 24 November 2014).

Lents, J., Davis, N., Osses, M., Nikkila, R. and Barth, M. (2004) 'Comparison of on-road vehicle profiles collected in seven cities worldwide', in *Transport and Air …*, pp. 1–24. Available at: http://issrc.org/ive/downloads/presentations/IVE_TAP_2004.pdf (Accessed: 16 July 2014).

Letshwiti, V., , Stanway, R. A. and and Mokonyama, M. (2003) 'Strategic Overview and Analysis of Vehicle Ownership Trends in South Africa With an Emphasis on Light Passenger Vehicles', *Statistics*, (July), pp. 1–9. Available at: http://repository.up.ac.za/dspace/bitstream/handle/2263/7448/Letshwiti_Strategic(2003).pdf;jsessionid=3A2D0CFFFD30AB33B659C55208F916F5?sequence=1.

Li, K., Liao, H., Mao, Y. and Ridley, D. A. (2016) 'Source sector and region contributions to concentration and direct radiative forcing of black carbon in China', *Atmospheric Environment*, 124, pp. 351–366. doi: 10.1016/j.atmosenv.2015.06.014.

Liland, K. H., Almøy, T. and Mevik, B. H. (2011) 'Optimal baseline correction for multivariate calibration using open-source software', *Applied Spectroscopy*, 43(4), pp. 13–16. doi: 10.1366/000370210792434350.

Liland, K. H. and Mevik, B.-H. (2015) 'baseline: Baseline Correction of Spectra'. Available at: https://cran.r-project.org/package=baseline.

Lim, S. S. *et al.* (2012) 'A comparative risk assessment of burden of disease and injury attributable to 67 risk factors and risk factor clusters in 21 regions, 1990-2010: a systematic analysis for the Global Burden of Disease Study 2010.', *Lancet*, 380(9859), pp. 2224–60. doi: 10.1016/S0140-6736(12)61766-8.

Liousse, C., Assamoi, E., Criqui, P., Granier, C. and Rosset, R. (2014) 'Explosive growth in African combustion emissions from 2005 to 2030', *Environmental Research Letters*, 9(3), p. 35003. doi: 10.1088/1748-9326/9/3/035003.

Lourens, A. (2012) *Air quality in the Johannesburg-Pretoria megacity: its regional influence and identification of parameters that could mitigate pollution/ASM Lourens*. North-West University. Available at: http://dspace.nwu.ac.za/handle/10394/8760 (Accessed: 28 February 2014).

Loveday, E. (2011) *Nigeria bans two-stroke engines, adopts Euro II emissions standards from 1996*, *Nigerian Observer*. Available at: http://green.autoblog.com/2011/08/31/nigeria-bans-two-stroke-engines-euro-ii-emissions-standards/ (Accessed: 19 November 2014).

Mamakos, A., Bergmann, A. D., Dardiotis, C., Florian, D., Sabbagh-Kupelwieser, N Schiefer, E., Schindler, W., Vescoli, V. and Winkler, G. (2014) 'Measurement of Automotive Particle Emissions within the European Legislative Framework : Status Quo and Future Trends', in *8th International Exhaust Gas and Particulate Emissions Forum*, pp. 16–31.

Mamakos, A., Bonnel, P., Perujo, A. and Carriero, M. (2013) 'Assessment of portable emission measurement systems (PEMS) for heavy-duty diesel engines with respect to particulate matter', *Journal of Aerosol Science*, 57, pp. 54–70. doi: 10.1016/j.jaerosci.2012.10.004.

Mapako, M., Oliver, D., Covary, N., Mdluli, T. and Musvoto, C. (2015) 'Selected environmental impacts of energy use by the automobile sector : Findings from a project focussed on Johannesburg and Cape Town Findings from a project focussed on Johannesburg and Cape Town .', (July 2015).

Marais, E. A. and Wiedinmyer, C. (2016) 'Air Quality Impact of Diffuse and Inefficient Combustion Emissions in Africa (DICE-Africa)', *Environmental Science and Technology*, 50(19), pp. 10739–10745. doi: 10.1021/acs.est.6b02602.

Matata, F., Kitali, A. and Sando, T. (2017) 'Operational characteristics of newly introduced bus rapid transit in Dar Essalaam, Tanzania', in *Transportation Research Board's 96th Annual Meeting*. Washington, DC. Available at: http://docs.trb.org/prp/17-06618.pdf.

Mbandi, A., Böhnke, J., Schwela, D., Vallack, H., Ashmore, M. and Emberson, L. (no date) 'Estimating vehicle fuel economy in Africa: A case study based on an urban transport survey in Nairobi'.

Mchomvu, Y. (2016) 'Establishment of Dar es Salaam BRT system-Phase 1'.

Merven, B., Stone, A., Hughes, A. and Cohen, B. (2012) *Quantifying the energy needs of the transport sector for South Africa: A bottom-up model*. Available at: www.erc.uct.ac.za/Research/publications/12-Merven-etal_Quantifying_energy_needs_transport sector.pdf.

Miller, A. L., Habjan, M. C. and Park, K. (2007) 'Real-time estimation of elemental carbon emitted from a diesel engine', *Environmental Science and Technology*, 41(16), pp. 5783–5788. doi: 10.1021/es070150a.

Ministry of Environment and Natural Resources (2015) *Kenya's Intended Nationally Determined Contribution (INDC)*. doi: 10.1007/s13398-014-0173-7.2.

Ministry of Transport Kenya (2011) *Feasibility study & Technical Assistance for Mass Rapid Transit System for the Nairobi Metropolitan Region*. Available at: http://nairobiplanninginnovations.files.wordpress.com/2012/05/nmrts-executive-summary-june2011.pdf.

Molaie, M., Falahian, R., Gharibzadeh, S., Jafari, S., Sprott, J. C. and Mattei, T. A. (2014) 'Artificial neural networks: powerful tools for modeling chaotic behavior in the nervous system', *computational nueroscience*. doi: 10.3389/fncom.2014.00040.

Nagendra, S. M. S. and Khare, M. (2005) 'Modelling urban air quality using artificial neural network', *Clean Technologies and Environmental Policy*, 7(2), pp. 116–126. doi: 10.1007/s10098-004-0267-6.

Nagpure, A. S. and Gurjar, B. R. (2012) 'Development and evaluation of vehicular air pollution inventory model', *Atmospheric Environment*. Elsevier Ltd, 59, pp. 160–169. doi: 10.1016/j.atmosenv.2012.04.044.

Ncube, M. (2012) *Urbanization in Africa*. Available at: http://www.afdb.org/en/blogs/afdb-championing-inclusive-growth-across-africa/post/urbanization-in-africa-10143/ (Accessed: 5 February 2014).

NEMA (2014) *The Environment management and coordination act (No.8 of 1999) The environment management and coordination (Air quality) regulations, 2014*. Kenya: National Environment Authority of Kenya. Available at: https://www.nema.go.ke/images/Docs/Regulations/Air Quality Regulations-3.pdf.

NHTSA (2014) *Summary of Fuel Economy Perfomance*, *U.S. Department of Transportation*. Available at: https://www.nhtsa.gov/sites/nhtsa.dot.gov/files/performance-summary-report-12152014-v2.pdf (Accessed: 16 September 2016).

Nissan Kenya (2017) *Nissan*. Available at: http://www.nissankenya.com/ (Accessed: 24 April 2017).

North, R. (2007) *Assessment of real-world pollutant emissions from a light-duty diesel vehicle*. Imperial College London. Available at: http://www.cts.cv.ic.ac.uk/documents/theses/northphd.pdf (Accessed: 10 February 2014).

Ntziachristos, L. *et al.* (2013) '1.A.3.b.i, 1.A.3.b.ii, 1.A.3.b.ii, 1.A.3.b.iv Passengers, light commercial trucks, heavy duty vehicles including buses and motor cycles', in *EMEP/EEA emission inventory guidebook 2013*.

Ntziachristos, L., Mellios, G., Tsokolis, D., Keller, M., Hausberger, S., Ligterink, N. E. and Dilara, P. (2014) 'In-use vs. type-approval fuel consumption of current passenger cars in Europe', *Energy Policy*, 67, pp. 403–411. doi: 10.1016/j.enpol.2013.12.013.

Oanh, N. T., Thuy Phuong, M. T. and Permadi, D. A. (2012) 'Analysis of motorcycle fleet in Hanoi for estimation of air pollution emission and climate mitigation co-benefit of technology implementation', *Atmospheric Environment*, 59, pp. 438–448. doi: 10.1016/j.atmosenv.2012.04.057.

Odhiambo, G. O. ., Kinyua, A. M., Gatebe, C. K. and Awange, J. (2010) 'Motor Vehicles Air Pollution in Nairobi , Kenya', 2(4), pp. 178–187.

Oh, Y., Park, J., Lee, J., Eom, M. Do and Park, S. (2014) 'Modeling effects of vehicle specifications on fuel economy based on engine fuel consumption map and vehicle dynamics', *Transportation Research Part D: Transport and Environment*, 32, pp. 287–302. doi: 10.1016/j.trd.2014.08.014.

Olvera, L., Plat, D. and Pochet, P. (2013) 'The puzzle of mobility and access to the city in Sub-Saharan Africa', *Journal of Transport Geography*. Elsevier Ltd, 32, pp. 56–64. doi: 10.1016/j.jtrangeo.2013.08.009.

Ommeh, M., McCormick, D., Mitullah, W., Risper, O. and Preston, C. (2015) 'The Politics Behind the Phasing Out of the 14-seater Matatu in Kenya', *University of Nairobi Digital Repository*, pp. 1–16. Available at: http://erepository.uonbi.ac.ke/handle/11295/85489.

Ong'uti, A. M. (2015) 'Road Infrastructure Gap: Kenya's Experience, 2000-2010', *International Journal of Applied Research*, 1(12), pp. 715–722.

Ou, X., Zhang, X. and Chang, S. (2010) 'Scenario analysis on alternative fuel/vehicle for China's future road transport: Life-cycle energy demand and GHG emissions', *Energy Policy*. Elsevier, 38(8), pp. 3943–3956. doi: 10.1016/j.enpol.2010.03.018.

Pandey, A. and Venkataraman, C. (2014) 'Estimating emissions from the Indian transport sector with on-road fleet composition and traffic volume', *Atmospheric Environment*, 98, pp. 123–133. doi: 10.1016/j.atmosenv.2014.08.039.

Pant, P. and Harrison, R. M. (2013) ‘Estimation of the contribution of road traffic emissions to particulate matter concentrations from field measurements: A review’, *Atmospheric Environment*, pp. 78–97. doi: 10.1016/j.atmosenv.2013.04.028 Review.

Penman, J., Gytarsky, M., Hiraishi, T., Irving, W. and Krug, T. (2006) ‘2006 IPCC Guidelines for National Greenhouse Gas Inventories-Overview’, *2006 IPCC Guidelines for National Greenhouse Gas Inventories*, 2(OVERVIEW), p. 12. doi: http://www.ipcc-nggip.iges.or.jp/public/2006gl/pdf/2_Volume2/V2_3_Ch3_Mobile_Combustion.pdf.

Petkova, E. P., Jack, D. W., Volavka-Close, N. H. and Kinney, P. L. (2013) ‘Particulate matter pollution in African cities’, *Air Quality, Atmosphere and Health*, 6(3), pp. 603–614. doi: 10.1007/s11869-013-0199-6.

PigiaMe (2017) *Cars for Sale in Kenya*. Available at: https://www.pigiame.co.ke/cars (Accessed: 24 April 2017).

Pillot, D., Legrand-tiger, A., Thirapounho, E., Tassel, P. and Perret, P. (2014) ‘Impacts of inadequate engine maintenance on diesel exhaust emissions’, in *Transport Research Arena 2014, Paris*.

Pirie, G. (2013) *Sustainable Urban Mobility in ‘ Anglophone ’ Sub-Saharan Africa*. Available at: http://www.unhabitat.org/grhs/2013.

Plotkin, S. (2004) ‘Fuel Economy Initiatives: International Comparisons’, in Cleveland, C. (ed.) *Encyclopedia of Energy Volume 2*. Elsevier, pp. 791–806.

Plotkin, S. (2016) ‘Fuel Economy Initiatives: A Worldwide Comparison’, in *Reference Module in Earth Systems and Environmental Sciences*. Elsevier. doi: 10.1016/B978-0-12-409548-9.01402-0.

Posada, A. F. and German, J. (2013) *Measuring in-use fuel economy in Europe and the US : Summary of pilot studies*. Available at: http://www.theicct.org/measuring-in-use-fuel-economy-summary-pilot-studies.

R core team (2016) ‘R: A language and environment for statistical computing.’ Vienna, Austria: R Foundation for Statistical Computing. Available at: https://www.r-project.org/.

Ramachandra, T. V. and Shwetmala (2009) ‘Emissions from India’s transport sector: Statewise synthesis’, *Atmospheric Environment*. Elsevier Ltd, 43(34), pp. 5510–5517. doi: 10.1016/j.atmosenv.2009.07.015.

Randu, E. K. (2013) *Determinants of Private Car Ownership in Kenyan Households*. Nairobi, Kenya. Available at: http://kippra.or.ke/index.php?option=com_docman&task=doc_view&gid=295&Itemid=.

Ribeiro, K. *et al.* (2007) ‘Contribution of Working Group III to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change’, in Metz, B., Davidson, O. R., Bosch, P. R., Dave, R., and Meyer, L. A. (eds) *Climate Change 2007: Mitigation.* Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, pp. 324–385. Available at: http://www.ipcc.ch/publications_and_data/ar4/wg3/en/ch5.html (Accessed: 7 February 2014).

Richardson, A. J., Ampt, E. S. and Meyburg, A. H. (1995) *Survey Methods for Transport Planning*. Eucalyptus. Available at: http://www.no2hcf.co.uk/docs/Traffic_survey_form.pdf.

Rivas, I. *et al.* (2017) ‘Identification of technical problems affecting performance of

DustTrak DRX aerosol monitors', *Science of The Total Environment*, 585, pp. 849–855. doi: 10.1016/j.scitotenv.2017.01.129.

Rodríguez, R. A., Virguez, E. A., Rodríguez, P. A. and Behrentz, E. (2016) 'Influence of driving patterns on vehicle emissions: A case study for Latin American cities', *Transportation Research Part D: Transport and Environment*, 43, pp. 192–206. doi: 10.1016/j.trd.2015.12.008.

Ropkins, K. (2016) 'pems.utils: Data handling, analysis and visualization tools for data from portable emissions monitoring systens and other mobile sources'. Available at: ftp://cran.r-project.org/pub/R/web/packages/pems.utils/pems.utils.pdf.

Ropkins, K., Beebe, J., Li, H., Daham, B., Tate, J., Bell, M. and Andrews, G. (2009) 'Real-World Vehicle Exhaust Emissions Monitoring: Review and Critical Discussion', *Critical Reviews in Environmental Science and Technology*, 39(2), pp. 79–152. doi: 10.1080/10643380701413377.

Ropkins, K., Li, H. and Burnette, A. (2016) *Next generation (Smaller, Lower cost, lower energy consumption) Portable Emissions Measurement Systems*, *6th International PEMS Conference and Workshop UCR CE-CERT*. Available at: http://www.cert.ucr.edu/events/pems/20 - PEMS2016.pdf (Accessed: 11 March 2017).

Roy, R. (2016) *The cost of air pollution in Africa*. 333. doi: 10.1787/5JLQZQ77X6F8-EN.

Salon, D. and Aligula, E. M. (2012) 'Urban travel in Nairobi, Kenya: Analysis, insights, and opportunities', *Journal of Transport Geography*. Elsevier Ltd, 22, pp. 65–76. doi: 10.1016/j.jtrangeo.2011.11.019.

Sandhu, G. and Frey, H. (2013) 'Effects of Errors on Vehicle Emission Rates from Portable Emissions Measurement Systems', *Transportation Research Record: Journal of the Transportation Research Board*, 2340, pp. 10–19. doi: 10.3141/2340-02.

SAPIA (2008) *Petrol and Diesel in South Africa and the impact on air quality*. Available at: http://www.sapia.co.za/_literature_86491/Petrol_and_Diesel_in_South_Africa_and_the_impact_on_air_quality,_November_2008.

Schipper, L. (2011) 'Automobile use, fuel economy and CO2 emissions in industrialized countries: Encouraging trends through 2008?', *Transport Policy*, 18(2), pp. 358–372. doi: 10.1016/j.tranpol.2010.10.011.

Schipper, L. and Fulton, L. (2009) 'Disappointed by Diesel ? The Impact of the Shift to Diesels in Europe through 2006', in *Energy and Global Climate Change 2009*, pp. 1–10. Available at: http://trid.trb.org/view.aspx?id=882117.

Schwela, D. (2012) 'Review of Urban Air Quality in Sub-Saharan Africa Region-Air Quality profile of SSA countries', *www-wds.worldbank.org*. Available at: http://www-wds.worldbank.org/external/default/WDSContentServer/WDSP/IB/2012/04/02/000386194_20120402015455/Rendered/PDF/677940WP0P07690020120Box367897B0ACS.pdf (Accessed: 31 January 2014).

SEI (2015) *GAP Forum Emissions Manual*. Available at: http://www.sei-international.org/gap-the-global-air-pollution-forum-emission-manual (Accessed: 28 April 2014).

Shilenje, Z., K, T., SO, P., P, N. and K, O. (2016) 'Roadside Air Pollutants along Elected Roads in Nairobi City, Kenya', *Journal of Geology & Geophysics*, 5(5). doi:

10.4172/2381-8719.1000253.

Shindell, D. *et al.* (2012) ‘Simultaneously Mitigating Near-Term Climate Change and Improving Human Health and Food Security’, 335(January), pp. 183–189.

Shindell, D., Faluvegi, G., Walsh, M., Anenberg, S. C., Van Dingenen, R., Muller, N. Z., Austin, J., Koch, D. and Milly, G. (2011) ‘Climate, health, agricultural and economic impacts of tighter vehicle-emission standards’, *Nature Climate Change*. Nature Publishing Group, 1(1), pp. 59–66. doi: 10.1038/nclimate1066.

Shindell, D. T. (2012) ‘Evaluation of the absolute regional temperature potential’, *Atmospheric Chemistry and Physics*, 12(17), pp. 7955–7960. doi: 10.5194/acp-12-7955-2012.

Sillaparcharn, P. (2007) ‘Vehicle Ownership and Trip Generation Modelling’, *IATSS Research*. International Association of Traffic and Safety Sciences, 31(2), pp. 17–26. doi: 10.1016/S0386-1112(14)60218-1.

Skeete, J.-P. (2017) ‘Examining the role of policy design and policy interaction in EU automotive emissions performance gaps’, *Energy Policy*. Elsevier, 104(November 2016), pp. 373–381. doi: 10.1016/j.enpol.2017.02.018.

Slavin, D., Abou-Nasr, A., Filev, D. . and Kolmanovsky, I. . (2013) ‘Empirical Modeling of Vehicle Fuel Economy Based on Historical Data’, *IEEE*, (313). Available at: http://ieeexplore.ieee.org/stamp/stamp.jsp?arnumber=6707111.

Smit, R., Brown, A. L. and Chan, Y. C. (2008) ‘Do air pollution emissions and fuel consumption models for roadways include the effects of congestion in the roadway traffic flow?’, *Environmental Modelling & Software*, 23(10–11), pp. 1262–1270. doi: 10.1016/j.envsoft.2008.03.001.

Smitk, K. and Akbar, S. (2012) ‘Air Pollution and Health in Rapidly Developing Countries’, in *Health damaging air pollution, a matter of scale*. Earthscan, p. 227. Available at: http://books.google.com/books?id=OBGLANLw3m8C&pgis=1 (Accessed: 19 November 2014).

Stohl, A. *et al.* (2015) ‘Evaluating the climate and air quality impacts of short-lived pollutants’, *Atmospheric Chemistry and Physics*, 15(18), pp. 10529–10566. doi: 10.5194/acp-15-10529-2015.

Streets, D. G., Bond, T. C., Lee, T. and Jang, C. (2004) ‘On the future of carbonaceous aerosol emissions’, *Journal of Geophysical Research D: Atmospheres*, 109(24), pp. 1–19. doi: 10.1029/2004JD004902.

Suh, H. H., Bahadori, T., Vallarino, J. and Spengler, J. D. (2000) ‘Criteria Air Pollutants and Toxic Air Pollutants’, *Environmental Health Perspectives*, 108(s4), pp. 625–633. doi: 10.1289/ehp.00108s4625.

Thompson, G. J., Carder, D. K., Besch, M. C., Thiruvengadam, A. and Kappanna, H. K. (2014) *In-use emissions testing of light-duty diesel vehicles in the United States*. Available at: http://www.theicct.org/sites/default/files/publications/WVU_LDDV_in-use_ICCT_Report_Final_may2014.pdf.

Tiege, U., Zacharof, N., Mock, P., Franco, V., German, J., Bandivadekar, A., Ligterink, N. and Lambrecht, U. (2015) *From laboratory to road*. Available at: http://www.theicct.org/sites/default/files/publications/ICCT_LaboratoryToRoad_2015_Report_English.pdf.

Tietge, U. and Diaz, S. (2017) *Cities driving diesel out of the European car market*. Available at: http://www.theicct.org/blogs/staff/cities-driving-diesel-out-european-car-market (Accessed: 16 August 2017).

Tietge, U., Mock, P., Franco, V. and Zacharof, N. (2017) 'From laboratory to road: Modeling the divergence between official and real-world fuel consumption and CO2 emission values in the German passenger car market for the years 2001-2014', *Energy Policy*. Elsevier, 103(January), pp. 212–222. doi: 10.1016/j.enpol.2017.01.021.

Total Motorcycle (2017) *Total Motorcyle Fuel Economy Guide in MPG and L/100km*.

Toubeau, C. (2016) *Dieselgate scandal symptomatic of how EU is losing its global regulatory crown, warns transport group*, *The parliement magazine*. Available at: https://www.theparliamentmagazine.eu/articles/opinion/dieselgate-scandal-symptomatic-how-eu-losing-its-global-regulatory-crown-warns (Accessed: 2 July 2017).

Toyota (2017) *Toyota global website*. Available at: http://www.toyota-global.com/ (Accessed: 24 April 2017).

Toyota Kenya (2014) *TOYOTA HIACE SPECIFICATIONS*. Available at: https://www.toyotakenya.com/products.php?products_id=49 (Accessed: 11 December 2014).

Toyota Kenya (2017) *Toyota Kenya Ltd*. Available at: https://www.toyotakenya.com/ (Accessed: 24 April 2017).

TÜV Nord (2013) *ICCT Fuel Economy data Collection Pilot Study*. Available at: http://www.theicct.org/sites/default/files/TNM_ICCT_FE_Data_Collection_Pilot_Study_ProjectReport_Final2.pdf (Accessed: 6 June 2016).

UC Riverside (2002) *Nairobi , Kenya Vehicle Activity Study*. Available at: www.issrc.org/ive/downloads/reports/NairobiKenya.pdf.

UN-DESA (2014) 'World Urbanization Prospects: The 2014 Revision, CD-ROM Edition'. Department of Economic and Social Affairs, Population Division. Available at: https://esa.un.org/unpd/wup/CD-ROM/.

UN-Habitat (2013) *Planning and Design For the Sustainable Urban Mobility-Global Report on Human Settlements 2013*. Edited by A. Amin et al. UN-HABITAT. Available at: http://www.unhabitat.org/pmss/listItemDetails.aspx?publicationID=3503.

UN-HABITAT (2014) *The State of African Cities 2014: Re-imagining sustainable urban transitions*. UN-HABITAT. doi: 10.2174/97816080506351100101.

UNEP (2011) *Near-term Climate Protection and Clean Air Benefits : Actions for Controlling Short-Lived Climate Forcers*. Nairobi, Kenya: United Nations Environmental Programme (UNEP). Available at: http://www.unep.org/pdf/Near_Term_Climate_Protection_&_Air_Benefits.pdf.

UNEP (2015) *Status of Fuel Quality and Vehicle Emission Standards : Sub Saharan Africa*. Available at: http://www.unep.org/Transport/new/PCFV/pdf/Maps_Matrices/Africa/matrix/SSAFuels_Veh_matrix_June2015.pdf (Accessed: 15 September 2015).

UNEP-PCFV (2014) *Status of Fuel Quality and Vehicle Emission Standards : Sub Saharan Africa Status*. Available at: www.unep.org/Transport/PCFV/pdf/Maps_Matrices/Africa/map/sulphur/MapSSAfricaSulp hur_April2014.pdf.

United Nations (1992) ‘United Nations Framework Convention on Climate Change’, *Fccc/Informal/84*, 1(3), pp. 270–277. doi: 10.1111/j.1467-9388.1992.tb00046.x.

United Republic of Tanzania (2016) *Final Draft: Natural Gas Utilization Master Plan 2016-2045*.

US-EPA (2015a) *EPA, California Notify Volkswagen of Additional Clean Air Act Violations*, *EPA*. Available at: https://www.epa.gov/newsreleases/epa-california-notify-volkswagen-additional-clean-air-act-violations (Accessed: 17 February 2017).

US-EPA (2015b) *Notice of Violation*. Available at: https://www.epa.gov/sites/production/files/2015-11/documents/vw-nov-2015-11-02.pdf (Accessed: 17 February 2017).

USAID (2000) *Cairo Air Improvement Project Vehicle Emission Testing Component-Motorcycle Emissions*. Available at: http://pdf.usaid.gov/pdf_docs/PNACY042.pdf.

Venter, C., Jennings, G., Hidalgo, D. and Pineda, A. F. V. (2017) ‘The equity impacts of bus rapid transit: a review of the evidence, and implications for sustainable transport’, *International Journal of Sustainable Transportation*, 8318(June), pp. 00–00. doi: 10.1080/15568318.2017.1340528.

Venter, C. and Mohammed, S. (2013) ‘Estimating car ownership and transport energy consumption : a disaggregate study in Nelson Mandela Bay’, *Journal of the South African Institution of Civil Engineering*, 55(1), pp. 2–10. Available at: http://www.scielo.org.za/pdf/jsaice/v55n1/01.pdf.

Venter, I. (2008) *SA must introduce new emissions standards by 2012, Toyota asserts*, *Engineering news*. Available at: http://www.engineeringnews.co.za/article/south-africa-must-introduce-new-emissions-standards-by-2012-toyota-asserts-2008-11-14 (Accessed: 19 November 2014).

van Vliet, E. D. S. and Kinney, P. L. (2007) ‘Impacts of roadway emissions on urban particulate matter concentrations in sub-Saharan Africa: new evidence from Nairobi, Kenya’, *Environmental Research Letters*. IOP Publishing, 2(4), p. 45028. doi: 10.1088/1748-9326/2/4/045028.

Volavka-Close, N. and Sclar, E. (2010) ‘Improving Population Health in a Rapidly Urbanizing World’, in *Urban Health perspectives vulnerable Populations*. Volvo Research Foundation. Available at: http://www.vref.se/publications/publications/improvingpopulationhealthinarapidlyurbanizingworld.5.11165b2c13cf48416deef.html (Accessed: 19 November 2014).

Wainberg, M., Foss, M. M., Quijano, D. and Gulen, G. (2017) *Current and Future Natural Gas Demand in China and India*.

Walsh, M. (2014) *Clean Fuels and Vehicles Regulatory Toolkit*. Available at: http://web.unep.org/transport/sites/unep.org.transport/toolkits/RegulatoryToolKit/docs/Clean_Fuels_and_Vehicles_Toolkit_Full_Report.pdf.

Wang, H., Fu, L., Zhou, Y. and Li, H. (2008) ‘Modelling of the fuel consumption for passenger cars regarding driving characteristics’, *Transportation Research Part D: Transport and Environment*. Elsevier Ltd, 13(7), pp. 479–482. doi: 10.1016/j.trd.2008.09.002.

Weiss, M. *et al.* (2012) 'Will Euro 6 reduce the NOx emissions of new diesel cars? – Insights from on-road tests with Portable Emissions Measurement Systems (PEMS)', *Atmospheric Environment*. Elsevier Ltd, 62(2), pp. 657–665. doi: 10.1016/j.atmosenv.2012.08.056.

Weiss, M., Bonnel, P., Hummel, R., Provenza, A. and Manfredi, U. (2011) 'On-road emissions of light-duty vehicles in Europe', *Environmental Science & Technology*, 45, pp. 8575–81. doi: 10.1021/es2008424.

WHO (2006) *WHO Air quality guidelines for particulate matter, ozone, nitrogen dioxide and sulfur dioxide: global update 2005: summary of risk assessment*. Geneva. Available at: http://apps.who.int/iris/handle/10665/69477 (Accessed: 13 February 2014).

WHO (2013) *Global status report on road safety report 2013*. Available at: http://www.who.int/violence_injury_prevention/road_safety_status/2013/en/.

WHO (2015) *Air quality in cities database*. World Health Organization. Available at: http://www.who.int/phe/health_topics/outdoorair/databases/en/ (Accessed: 16 February 2014).

WHO (2016) *WHO Global Urban Ambient Air Pollution Database (update 2016)*, *WHO*. World Health Organization. Available at: http://www.who.int/phe/health_topics/outdoorair/databases/cities/en/ (Accessed: 29 September 2016).

Wicking-Baird, M., Villiers, M. De and Dutkiewicz, R. K. (1997) 'Cape Town brown haze study', 8(4), pp. 121–125. Available at: http://journals.co.za/content/jesa/8/4/AJA10161686_275?fromSearch=true (Accessed: 26 May 2014).

Wood, S. (2017) 'Mixed GAM Computation Vehicle with GCV/AIC/REML Smoothness Estimation'. doi: 10.1186/1471-2105-11-11.Bioconductor.

World Bank (2014) *Africa Development Indicators | Data*. Available at: http://data.worldbank.org/data-catalog/africa-development-indicators (Accessed: 16 February 2014).

Wu, T., Zhao, H. and Ou, X. (2014) 'Vehicle ownership analysis based on GDP per capita in China: 1963-2050', *Sustainability (Switzerland)*, 6(8), pp. 4877–4899. doi: 10.3390/su6084877.

Yanowitz, J., Graboski, M. S., Ryan, L. B. A., Alleman, T. L. and McCormick, R. L. (1999) 'Chassis dynamometer study of emissions from 21 in-use heavy-duty diesel vehicles', *Environmental Science and Technology*, 33(2), pp. 209–216. doi: 10.1021/es980458p.

Yao, Z., Wei, H., Liu, H. and Li, Z. (2013) 'Statistical Vehicle Specific Power Profiling for Urban Freeways', *Procedia - Social and Behavioral Sciences*. Elsevier B.V., 96(Cictp), pp. 2927–2938. doi: 10.1016/j.sbspro.2013.08.324.

Zachariadis, T., Ntziachristos, L. and Samaras, Z. (2001) 'The effect of age and technological change on motor vehicle emissions', *Transportation Research Part D: Transport and Environment*, 6(3), pp. 221–227. doi: 10.1016/S1361-9209(00)00025-0.

Zhang, K. (2006) *Micro-scale on-road vehicle-specific emissions measurements and modeling*. North Carolina State University. Available at: https://repository.lib.ncsu.edu/bitstream/handle/1840.16/5098/etd.pdf?sequence=1&isAllowed=y (Accessed: 31 January 2017).

Zhang, K. and Frey, C. (2005) ‘Road Grade Estimation For On-road Vehicle Emissions Modelling Using LIDAR Data’, in *Annual Meeting of the Air & Waste Management Association*. Minneapolis, pp. 1–22. Available at: http://www4.ncsu.edu/~frey/conf_pr/Zhang_Frey_2005.pdf.

Zhang, S., Wu, Y., Liu, H., Huang, R., Un, P., Zhou, Y., Fu, L. and Hao, J. (2014) ‘Real-world fuel consumption and CO2 (carbon dioxide) emissions by driving conditions for light-duty passenger vehicles in China’, *Energy*, 69, pp. 247–257. doi: 10.1016/j.energy.2014.02.103.

Zhang, S., Wu, Y., Liu, H., Ruikun, H., Yang, L. and Li, Z. (2014) ‘Real-world fuel consumption and CO2 emissions of urban public buses in Beijing’, *Applied Energy*, 113(January 2014), pp. 1645–1655. doi: 10.1016/j.apenergy.2013.09.017.

Zheng, X. *et al.* (2015) ‘Characteristics of On-road Diesel Vehicles: Black Carbon Emissions in Chinese Cities Based on Portable Emissions Measurement’, *Environmental Science and Technology*, 49(22), pp. 13492–13500. doi: 10.1021/acs.est.5b04129.