The potential role of walking and cycling to increase resilience of transport systems to future external shocks.

Creating an indicator of who could get to work by walking and cycling if there was no fuel for motorised transport

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

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Section 1 and 2 are used in the literature review Chapters 2 and 3. Section 3 of the paper is used in Section 4.2 of the thesis and Section 4 of the paper is used in the indicator design in Section 4.3 of the thesis.

I was the principal author of this paper. My Co-authors are my PhD supervisors. Their input was principally in terms of advice, discussion and feedback on drafts of the paper. At the time of thesis submission, this paper is also being reviewed for publication by the journal Case Studies on Transport Policy.

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My contribution to this paper was Section 2. It is the Section of the paper examining conceptualisations of resilience. It includes text from and is based on Section 2.3 of Chapter 2.

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Abstract

There are finite limits to resources, both extractable raw materials and planetary life support resources. Because of this, it is possible that there will be a severe and long lasting reduction in the fuel available for motorised transport which could manifest itself suddenly as a *fuel shock*. This thesis is concerned with the conceptual design, methodological development and application of a new spatially explicit transport policy indicator which estimates: Who could get to work tomorrow by walking and cycling if there was a fuel shock today? This thesis estimates the potential that walking and cycling have to increase resilience to fuel shocks in the period immediately after the fuel shock.

A conceptual model of resilience to fuel shocks by individuals was devised. A novel hybrid static spatial microsimulation technique was developed. It was used to generate a population of individuals with the appropriate attributes to estimate for large populations the capacity to make journeys using only walking and cycling. This modelling process is generic and can be used to generate indicator results wherever suitable data exist. Using a simple scenario of a fuel shock which occurs today, current data could be used to estimate the indicator. A case study using the census data covering England, the Health Survey For England and other data sets was produced. Validation of the modelling process informs the analysis of the results.

The results demonstrate the ability of the indicator to show variation between areas, in both a base case and when specific policy measures are applied. The base case indicator estimated that nationally in England only 44% (±4.85%) of individuals have capacity to commute to work by walking and cycling following a fuel shock. A local analysis of Leeds identified the spatial patterns of attributes which influence the indicator, allowing greater understanding of the geographical influences on capacity to travel by active modes. A policy package increasing bicycle availability, health and fitness and ensuring the ability of children to travel to school without needing adult escort was found to have a significant effect in 99% of English Output Areas.

The indicator calculation methodology has produced significant improvements in the estimation of capacity to travel by active modes. Assuming everyone can cycle 8km (a common assumption in transport planning) overestimates capacity of the population to commute by active modes. The indicator identified a mean difference of 26% across all OAs.

By considering constraints the indicator estimates of mean maximum distance travel distance by active modes differ by 73% compared to methods which ignore constraints.

The indicator produced is policy relevant; The indicator can be judged as a good indicator when assessed against criteria for good indicators established by other workers. The modelling process is generic and can be applied to other scenarios. The results were presented at different extents and resolutions; making a useful and flexible spatially explicit indicator tool.

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1 Introduction

This thesis is the result of an ESPRC CASE studentship which is funded in partnership with UK NGO Sustrans[1]. The research presented is based upon defining and assessing the assertions made by Sustrans below.

Sustrans believes that there is link between sustainable transport modes (walking and cycling) and resilience of transport systems to 'shocks' in the context of a finite limit to resources. Sustrans further believes that planning models are needed to reflect the positive impacts of sustainable transport policies and sustainable modes on resilience. Sustrans' claims are not taken at face value nor are they without foundation. Sustrans' position infers the points below. Assessing evidence to support these claims is outlined in Section 1 and examined in depth within the literature review.

- Shocks may be described as unusual or novel events which have negative consequences.
- Finite limits to resources are seen as the root causes of shocks (assessed in Section 2.2)
- Resilience in the statement above infers the ability to cope with shocks (resilience is examined in Section 2.3).
- One particular type of shocks are transport fuel shocks (referred to after this as a fuel shock). They are a sudden and severe reduction in availability of fuel for motorised transport which signals a permanent reduction in fossil fuel availability for motorised transport. The root cause of fuel shocks is finite limits to resources (discussed in Section 2.2).
- Planning models rely upon indicators; clear and transparent simplifications which aid representation of the transport system across a wide area (discussed in Sections 3.1 and 3.2).

1.1 Justification of research

This thesis concerns designing and developing methods to calculate and apply a new spatially explicit transport policy indicator which shows: Who could get to work tomorrow by walking and cycling if there was a fuel shock today? This thesis estimates the potential that walking and cycling have to increase resilience to fuel shocks in the period immediately after the fuel shock. To justify development of this indicator, fuel shocks have to be

[1] http://www.sustrans.org.uk/about-us

possible and there has to be policy value in studying the effects of a hypothetical fuel shock which occurs today.

There is potential for fuel shocks due to the fact that there are finite limits to resources. There are finite limits to the quantity of each form of fossil fuel held in the ground expressed by the concept of Peak-oil (Aftabuzzaman and Mazloumi, 2011; Chapman, 2014). Estimates have been made of the finite nature of the resources to support human life and quality of life (Rockstrom et al., 2009). Rockstrom et al argue that the safe limits of some key resources which support human quality of life have been exceeded (e.g. the climate system) and that this is due principally to the industrialisation of humanity and its dependence upon fossil fuels. This infers that there is a need to drastically reduce fuel use to ensure human quality of life (see for example Berners-Lee and Clark, 2013).

Finite limits to resources show that there is evidence that a severe reduction in fuel availability may occur though much uncertainty over where and when. For example there is uncertainty as to when Peak-oil may occur (Chapman, 2014) and there is continuing debate on the forecast rate of global climate change (IPCC, 2013). There is also uncertainty over whether finite limits to resources would lead to a gradual decline in fuel availability in a particular location or a fuel shock – a step change in fuel availability rapidly moving from current fuel availability to no fuel availability for motorised transport. However there is a rationale for investigating shocks based on previous work by others: there have been a number of scenarios[2] developed which provide a logical rationale for fuel shocks e.g. (Curry, 2006) and secondly workers who have argued in support of rapid changes (e.g. Diamond, 2006; Urry, 2010).

It is acknowledged that the probability of a fuel shock occurring today is very small. However, there is policy value to considering a fuel shock that happens today. Banister and Hickman, (2013) note several advantages of asking what-if questions about severe forced changes to the transport system, they:

- Encourage thinking about longer term possibilities
- Broaden the range of options considered
- Acknowledge uncertainty and the fragility of forecasts based on current trends – this helps to anticipate the unexpected

[2] “scenarios are logical narratives dealing with possibly far-reaching changes” (Gallopin, 2002).

A fuel shock today is a conceptually easy to understand starting point for discussing possible futures and appropriate policies. This argue Banister and Hickman, (2013) is important in transport. This is because firstly it illustrates opportunities for major changes in policy direction and stimulates discussion. Stimulating discussion is an important and positive function of policy tools (Boulanger, 2007). Secondly, because an indicator based on the assumption of a fuel shock today can be grounded in current data, it allows tools developed in academic research to aid planning by practitioners and policy makers.

The justification for investigating resilience to fuel shocks requires only that there is evidence that fuel shocks *could* occur. It is not necessary to predict the timing of fuel shocks in order to consider resilience. Transport is particularly dependent upon oil (Schiller et al., 2010). Restriction in the availability of fossil fuels in general or oil specifically would affect the transport system. Having the capacity to walk and cycle to access destinations and activities clearly offers a form of resilience to fuel shocks as these modes do not require fossil fuels. Resilience based on walking and cycling is also not dependent on new technological innovations. This is a potentially robust and sustainable form of resilience because as Beck, (1992) and Giddens, (1999) argue, relying purely on technological innovation frequently creates new problems; for example the invention of steam and internal combustion engines led to the large scale use of fossil fuels which in addition to the observed benefits created risks to society. This forms the second justification for the research: Walking and cycling offer a robust sustainable form of resilience to fuel shocks. A third practical justification for research into resilience to fuel shocks is policy relevance: If there is a possibility of a transport fuel shock, then a measure of resilience to fuel shocks is a useful input to any form of anticipatory planning. It is assumed that transport system resilience can be enhanced if there is greater knowledge of the level of resilience to fuel shocks. The fourth justification for the research is that resilience to fuel shocks is important but there are problems considering it in policy because of a lack of satisfactory indicators. Authorities in the UK for example wanting to assess resilience to fuel shocks do not have a suitable estimation method or indicator for doing so. Current indicators are not able to give a practical measure of the adaptive capacity element of resilience. Adaptive capacity to fuel shocks includes the ability to continue making journeys post shock, but by substituting the pre-shock mode for walking and cycling. Particularly, there are no existing indicators that are sensitive to a variety of policy measures affecting fitness, obesity, bicycle availability and bicycle infrastructure whose impacts (at least in the short term) are on a smaller scale than large-scale land use and urban morphology change[3].

1.2 Aim

The aim of this thesis is to estimate the potential for walking and cycling to enhance resilience to fuel shocks and introduce it as a factor into multi-objective strategic transport planning.

1.3 Objectives

The objectives of the research relate to producing an indicator which can be assessed as a 'good' transport indicator against previously defined indicator quality standards defined by Marsden et al., (2006) which performs the two key useful functions of indicators: That of being able to contribute to planning models as a decision making tool and also a means to demonstrate need for change of transport planning goals or strategy (Boulanger, 2007; Gudmundsson, 2010).

The objectives are:

1. To develop a generic approach to estimating indicators of resilience to transport fuel shocks.

2. To develop a static spatial microsimulation based method of implementing, for large populations, a model of capacity to make journeys using only walking and cycling which can be used to generate indicator results.

3. Test the applicability of the indicator design and modelling methods to real data. This will be achieved by integrating a range of secondary data sources from England to report results at both fine and coarser geographies (Output Areas[4] and coarser geographies in the UK hierarchy).

4. Test the ability of the indicator to show variation between areas in both a base case and when specific policy measures are applied, and consequently report the effectiveness of the tested policies at increasing the resilience to fuel shocks by promoting adaptive capacity by walking and cycling.

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[3] Small scale changes may be more effectively targeted at specific people, communities or places, bringing benefits in terms of cost effectiveness and social impact.

[4] Output Areas are the smallest spatial units used for dissemination of aggregate UK census data. Further information is given in Chapter 7.

1.4 Introduction to the scope of the indicator

The approach of the work is to develop an indicator of adaptive capacity to fuel shocks; it ***does not predict journey behaviour***. Indicators help provide understanding of a situation of interest (Mitchell et al., 1995). Indicators are not themselves predictive. The situation of interest may be based on either: the present time using current data, a scenario or a predictive model of the future. Before indicators are calculated, a separate process is required to define the situation of interest. The outputs of this process are used as inputs to the indicator calculation process. This is a fairly simple idea, commonly found in transport planning. In this thesis the situation of interest is defined by a simple scenario in which a fuel shock occurs today and adaptive capacity is estimated immediately after the shock.

The situation of interest in this thesis is a simple scenario; a fuel shock which occurs today. The reasons for this are: Even though this situation is unlikely it is of policy interest. Chapter 2 establishes that fuel shocks are a sufficient threat to be taken seriously in transport planning. Imagining major forced changes aids consideration of major changes in policy direction (Banister and Hickman, 2013). Secondly, if the scenario assumes a fuel shock occurs today current data may be used. Using current data means that there is no need for a predictive model of the future to define the situation of interest and consequently no need to speculate about the attributes of individuals at the time of the shock. Thirdly, an indicator based on this simple scenario, results in a base case indicator, which can be compared to counter factual policy case in the same scenario. It could also be compared to indicators based on a different situation of interest produced in future work. This is discussed further in Section 4.2.

For purely practical reasons the indicator is based upon a model of adaptive capacity the ‘morning after’ a shock which happens tomorrow. On the ‘morning after’ the shock, the number of ways in which people can adapt is likely to be limited to changing modes. For example, people are unlikely to be able to move home to a better location or get a new job the morning after, nor can land-use and location of jobs and services be changed instantly. The ‘morning after’ is chosen not for policy reasons, but for the practical reason that a calculable (based on current data), relatively non-controversial, and transparent indicator can be produced for this point in time.

Many forms of adaptive capacity are not possible immediately following a fuel shock. The decision to estimate adaptive capacity immediately after a shock also avoids the need for controversial assumptions about attitude and behaviour change (or not) resulting from shocks. For these reasons it does not forecast the *propensity* to walk and cycle following a fuel shock. The indicator considers one aspect of adaptive capacity: Attempting a comprehensive assessment of every different form of adaptive capacity would have been less useful as an indicator. Also, attempting to measure every facet of resilience would be complex, require a great deal of data, require speculation about human behaviour, be impractical to calculate for many areas and outputs may be so complex so as to not offer practical help to decision makers.

The indicator defines a fuel shock as a permanent reduction in fuel availability. An indicator of capacity to get to work by walking and cycling is particularly relevant in a fuel shock. Its usefulness is uncontroversial. However in a short term fuel disruption other forms of adaptation such as stock piling fuel may be *argued* to be more appropriate. Including short term disruptions would then create uncertainty over whether the indicator I have developed is appropriate. For this reason, in this thesis, short term disruptions to fuel supply are beyond the scope of the work.

The *modelling process* used to calculate the indicator involves a spatial microsimulation method for improving estimation of the maximum walking and cycling distance of an entire population of individuals. The *modelling process* is not limited to being applied to just one indicator. It could, in future, be adapted and applied to other fuel shock scenarios and even completely different indicators such as response to short term fuel disruptions; if that is found to be appropriate. However, to reiterate, the focus of this thesis is the development of an indicator of the potential for walking and cycling to increase resilience to fuel shocks.

1.5 The structure of the thesis

This thesis consists of three components shown in Table 1.1

Table 1.1 Components of the thesis

Component	Chapters	Objectives
Conceptual approach A conceptual approach and design of an indicator of resilience of people to fuel shocks	2-4	1
Methodology A method to calculate the capacity make a specific journey using only walking and cycling on a network with no motor vehicles.	5-6	2
Application An application of the method to calculate the indicator of the potential for walking and cycling to offer resilience to fuel shocks at fine resolution for the whole of England.	7-9	3-4

The literature review is split over Chapters 2 and 3. In Chapter 2, evidence for fuel shocks and definitions of resilience, which may be relevant to fuel shocks, are examined. In Chapter 3 previous work is examined to answer these questions:

- What is currently being done within transport planning to consider a) Fuel shocks? b) Resilience? c) Resilience to fuel shocks in transport planning – Are there current indicators of adaptive capacity to fuel shocks?
- How are transport planning decisions made?
- What modelling and indicator tools are used in transport planning?

Chapter 4 details the scope of the indicator which was outlined above and based on this presents a conceptual indicator design. It is based on the pre-requisites for indicators in transport policy defined in Chapter 3. A diagrammatic representation is made of the factors which influence the indicator. There is also an explanation of the determinants of resilience to fuel shocks.

Chapter 5 discusses methods which could be used to implement the conceptual indicator design. The modelling process has to capture the variation inherent in the real population so that it can show variation between small areas such as UK Output Areas as well as coarser spatial units in both a base case[5] and when specific policies are applied. Static spatial microsimulation is found to be a suitable methodology to include in the modelling process. This is because it can capture an appropriate range of individual variation in the attributes affecting resilience and adaptive capacity to fuel shocks. Spatial microsimulation allows the combining of detailed information about individuals from one source, combined with small area aggregate data from another (Ballas et al., 2005b; Hermes and Poulsen, 2012; Tanton and Edwards, 2013a). Literature on the use and performance of these techniques is reviewed to select suitable techniques. A need for a novel two stage hybrid spatial microsimulation technique is identified. Chapter 5 also discusses methods to make quantitative estimates of attributes such as bicycle pedalling power which are also required in the modelling process.

Chapter 6 explains the methods used to construct the indicator. These methods are generic; they could be applied to suitable data in any country, not just the English case study data described in Chapter 7. A formal definition of the indicator is given using mathematical notation to describe the relationship between the attributes which are used to calculate the indicator. The method of population synthesis is explained. A novel two stage hybrid method is used; firstly a Simulated Annealing based Combinatorial Optimisation method is used to allocate attributes to create synthetic individuals. In the second stage, Monte-Carlo sampling is used to allocate additional attributes not available in the sample population. A flow chart summarising the calculation of the indicator and a list of simplifying assumptions is also given.

Chapter 7 describes the data used to make a case study which calculates the indicator for 165665 English Output Areas principally using 2001 UK census data and the Health Survey for England. Issues faced which were overcome are discussed. There are also explanations of simplifying assumptions and limitations arising from the choice of data.

Chapter 8 discusses model validation and sensitivity testing. The first section covers validation of the spatial microsimulation, that is the extent to which the synthetic population is a realistic representation of the actual

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[5] The base case is the adaptive capacity situation tomorrow with no extra intervention

population. The second section examines the sensitivity of the model which calculates the indicator. Sensitivity to assumptions are tested such as the time budget of individuals along with sensitivity to unknown factors such as the distribution of bicycle type (the tyres of which have differing rolling resistance and affect maximum travel distance). Limitations of the methodology and data are summarised based on the findings of model testing but it is found that the indicator values derived from the model can be used to inform policy.

Chapter 9 describes and analyses indicator results that may be used to inform policy. Base case results are presented first and then the effects of hypothetical policies are described. The model produces results which allow discrimination of indicator values between locations and shows where policy interventions are likely to have significant effects. The methods used allow results to be given as a national or local level indicator. For example results could be aggregated to district zones so that a national government department could allocate resources to least resilient districts. Local authorities could be given indicator results at Output Area resolution in order to target resources at Output Areas within the district with low levels of resilience. Local analysis is carried out using Leeds as a case study. Individual level modelling also allows segmentation of the population to a certain extent to identify particularly vulnerable age groups for example. Comparison of the indicator outputs is made with the Index of Multiple Deprivation (IMD). This contextualises the indicator; it suggests areas where indicator values are low and deprivation is high which is a simple proxy for areas most likely to suffer disadvantage and exclusion in the event of a fuel shock. This demonstrates usefulness of the indicator and also suggests further work.

Chapter 10 justifies the conclusion that the objectives of the thesis were met and acknowledges limitations. There are suggestions for further work, some based upon addressing limitations identified in this study and others which raise questions of interest which were beyond the scope of this study.

2 Fuel shocks and resilience

2.1 Introduction

As explained in the introduction, the UK NGO Sustrans believes that there is link between sustainable transport modes (walking and cycling) and resilience of transport systems to 'shocks' in the context of a finite limit to resources. Sustrans further believes that planning models are needed to reflect the positive impacts of sustainable transport policies on resilience.

- Shocks may be described as unusual or novel events which have negative consequences. Finite limits to resources are seen as the root causes of shocks
- Resilience in the statement above infers the ability to cope with shocks.

The literature review in this thesis is in two parts covering chapters 2 and 3. It examines Sustrans' statement as follows:

Chapter 2: Fuel shocks and resilience: In part 1 of the literature review, previous work is examined to answer these questions:

- What evidence is there for the possibility of fuel shocks?
- What conceptualisations of resilience exist and could they express the concept of resilience to fuel shocks?

Chapter 3: Transport planning and indicators of adaptive capacity: In part 2 of the literature review, previous work is examined to answer these questions:

- What is currently being done within transport planning to consider
    a. Fuel shocks?
    b. Resilience?
    c. Resilience to fuel shocks in transport planning – Are there current indicators of adaptive capacity to fuel shocks?
- How are transport planning decisions made?
- What modelling and indicator tools are used in transport planning?

2.2 Fuel shocks

There is literature that suggests several different potential causes of fuel shocks:

Underlying or root causes of fuel shocks

- Finite limits to extractable resources e.g Peak-oil

- Finite limits to resources providing planetary life support systems e.g. damage to climate systems by CO_2 emissions.

Trigger causes of fuel shocks

- Natural disasters
- Economic crisis
- War
- Political change

Each of these will be discussed in the coming sections. In addition scenarios of future fuel availability have been developed by several researchers which argue that a fuel shock is plausible. These are discussed in 2.2.4.

2.2.1 Finite limits to extractable fuel resources: Peak-oil

Peak-oil is a model of the production of oil over time. The point at which oil production reaches its maximum is called ‘Peak-oil ’ and after that point it declines. The model was originally proposed by Hubbert, (1956). The model gained credibility by accurately predicting the peaking of US Oil production in 1971 (Bowden, 1985; Chapman, 2014; Hubbert, 1971). If demand for oil is still increasing as the supply of oil begins to decrease then there will be a gap between demand and supply of fossil fuels for transport. This is a potential cause of fuel shocks (Krumdieck et al., 2010; Lang and Dantas, 2010).

There is an ongoing debate about whether there will be a global peak in oil production and if so when it would happen. There is considerable support for the theory of Peak-oil , for example Chapman, (2014) cites 16 sources which suggest a date for Peak-oil, Aftabuzzaman and Mazloumi, (2011) cite another nine and there are others for example Kerr,(2011) and Owen et al., (2010). The number of studies alone does not prove a theory. Additionally, there is disagreement over when Peak-oil will occur amongst the theory’s advocates. The average date for Peak-oil suggested by the studies reported in Aftabuzzaman and Mazloumi, (2011) is 2014. Chapman, however, splits the studies he cites into several categories. Those with an ‘early date for Peak-oil (average date 2010), those with a ‘late date for Peak-oil (average date 2028). There are additional studies suggesting both early dates (Kerr, 2011) and later dates (Owen et al., 2010).

There are also reports which doubt a peak will occur (e.g.BP, 2012; Maugeri, 2012; Shell, 2013) though these reports come from two oil companies and a former oil executive. There are 3 main arguments against the theory of

Peak –oil. Firstly, reserve estimates claim there is enough oil for decades. Proven oil reserves at the end of 2012 were estimated at 1668.9 billion barrels. This equates to 52.9 years of supply according to BP (2012). In the past decade proven oil reserves have increased by 26% (BP, 2012) suggesting continued new discoveries. The counter to this is that there are several different methods used to measure reserves; so there is not one consistent and therefore reliable measure. There are benefits to over-reporting oil reserves. For example OPEC countries are allowed to sell more oil if they have larger reserves thus incentivising exaggerated reserve estimates (Chapman, 2014). Oil reserves are classified as state secrets in Russia so this is an example of data being difficult to obtain (Chapman, 2014). These points suggest that there is at the very least uncertainty as to the amount of oil available. Therefore a fuel shock caused by Peak-oil cannot be ruled out as a possibility.

The second argument is that Peak-oil will not be relevant because oil that is currently not classed as a proven or possible reserve could be extracted by improved technology in the future. This claim is made by Maugeri, (2012) and EIA, (2010). Improved technology is a possibility, but its deployment is not a certainty so therefore this also does not rule out the possibility of a fuel shock caused by Peak-oil .

The third argument against the possibility of Peak-oil is that substitution will render the Peak-oil question irrelevant. This argument concerns substitution of oil for renewables and oil for other fossil fuels. Demand for alternative energy will increase and demand for oil will decrease thus avoiding the problems of Peak-oil. This view is based on the analysis of an IPCC forecast suggesting up to 77% of global energy being produced by renewables by 2050 and applied to oil demand forecasts (Chapman, 2014). Again this is a possibility not a certainty thus still allowing for the possibility of Peak-oil generated fuel shocks. This claim is also not geographically specific; 77% of energy supply in every country is different to a claim that some countries will derive 77% of their energy from renewables whilst others are still heavily dependent upon oil. Some countries may not be able to substitute energy supplies, again leaving the possibility of Peak-oil affecting fuel availability in specific countries. Part of the Peak-oil argument relating specifically to transport is that because of the dominance of the internal combustion engine transport is ‘tied in’ to oil use and substitution is more difficult (Helm, 2011). There is much debate on the practicality of electrifying the car fleet or substituting oil for hydrogen. There are many optimists (IEA,

2013) but also warnings that electrification on such a huge scale will cause other resource criticality problems; for example a shortage of rare earth metals for batteries and motors (Roelich, 2012). The issue of substitution is contested and models of resource criticality are in development (e.g. Knoeri et al., 2013; Roelich et al., 2014) but the uncertainty cannot completely rule out the possibility of a Peak-oil caused fuel shock.

2.2.2 Finite limits to resources providing planetary life support systems

Rockstrom et al., (2009) argue that continued high levels of fossil fuel use could cause damage to the key bio-physical systems on Planet Earth which create a desirable environment for human life and development. This means that there is an argument for drastically reducing fossil fuel use. Rockstrom et al., (2009) propose that nine key bio-physical systems and associated thresholds be used to quantify key boundaries, which if crossed could lead to "unacceptable environmental damage". They explain what they mean by describing the Holocene period. It is the most recent period in geological time – which began at the end of the last glacial period, approximately 10,000 years ago. For most of this time, global environmental conditions have been very conducive to human development. Human civilisation has developed in the Holocene period. They argue that continued development of human society is dependent on the continuation of the Holocene environmental conditions. However, "*The exponential growth of human activities is raising concern that further pressure on the Earth System could destabilize critical biophysical systems and trigger abrupt or irreversible environmental changes that would be deleterious or even catastrophic for human well-being*" *(Rockström et al., 2009 p2).* The key thresholds are based on the maximum change which can occur in relation to the Holocene state (Rockström et al., 2009). They tentatively suggest indicators for the states of seven of these systems. Three of these systems have they argue, already exceeded safe limits. The first of these key systems is climate change – for which their indicator is CO_2 concentration. They argue that CO_2 levels leading to greater than 2^oC change will result in significant damage to human quality of life. The 2^oC increase in temperature is a commonly agreed threshold beyond which the likelihood of negative consequences is high (UNFCCC, 2011). UNEP assessments of emissions data suggest that global emissions which are currently growing must peak before 2020 in order to have a medium or better chance of not exceeding a global temperature rise of 2^oC (UNEP, 2011). This target translates to a maximum cumulative emissions of around

1000 Giga tonnes of CO_2 based on climate and carbon cycle models for example those used by the IPCC (IPCC, 2013). There is potential for considerably higher emissions than this if all proven fossil fuel resources were burned. Hansen et al., (2013) compile reserve estimates from multiple sources. Resources which are economic to extract using current technologies have potential emissions of approximately 1800 Giga tonnes of CO_2, with some of their data suggesting total potential emissions of unconventional gas alone of over 15000 Giga tonnes of CO_2. They acknowledge uncertainty in their sources but even with significant margin of error there is evidence for fossil fuels to cause global warming greater than 2^oC. Hansen et al., (2013) infer from their models that cumulative emissions of 500 giga-tonnes of carbon ought to be the maximum “safe” limit. Arguments that fossil fuels should remain in the ground to prevent damage to climate and other planetary support systems are made for example by Berners-Lee and Clark, (2013); Helm, (2011); Le Page, (2013); McGlade and Ekins, (2014) These arguments suggest that Rockstrom et al’s threshold is not unrealistically radical.

Biodiversity loss is another key system where Rockstrom et al argue a key threshold has been exceeded. There is evidence of continued bio-diversity loss (e.g. Cardinale et al., 2012; Pereira et al., 2010). The bio-diversity indicator is species extinctions per year. Rockstrom et al., (2009) argue biodiversity loss has negative effects on climate change, and that extinction of particular species can cause ecosystems to collapse. This could affect cycling of nutrients and other life supporting chemicals, which may for example affect human food production. The third threshold they claim has been exceeded relates to the removal of Nitrogen from the atmosphere: Nitrogen removed from the atmosphere once converted into to fertilizer reacts with the environment, becoming a pollutant, impacting on ecosystems and the climate system.

If fossil fuels damage planetary life support systems then there is a case for restricting fossil fuel use through policy. If this occurred then it would greatly reduce fuel available for motorised transport. Some criticisms of the planetary boundaries approach of Rockstrom et al are that thresholds encourage business as usual until every threshold is exceeded. Additionally there is concern that some of the thresholds such as freshwater use and bio-diversity loss are too generous (Nature, 2009). If the scientific argument that the planetary boundaries described are critical is correct and it is acted upon, then it could lead to a reduction in fuel available for motorised transport. If as critics suggest, no action is taken but the scientific argument is correct then some places which were habitable become less so. This may have knock on consequences such as migration, conflict and economic and political turmoil all of which have potential to cause reduction in availability of fuel in particular countries.

Finite limits to both extractable resources and planetary life support systems seem to be the potential root causes of fuel shocks and the assertion that these interacting problems is a potential cause of fuel shocks and other impacts on quality of life is also made in Urry, (2010) and Hopkins, (2008).

2.2.3 Other causes of fuel shocks / trigger causes of fuel shocks

Issues which have caused fuel supply disruptions in the past may act in concert with the finite resource limits above to cause fuel shocks. There are many potential causes of disruptions to fuel supply: e.g. natural disasters, extreme weather events, war, protest and strikes. These have short to medium term impacts but once the event has passed fuel supply can resume. However if these causes of disruption act in concert with the root-causes of fuel shocks this may determine the geography of where fuel shocks occur.

The scale of effect of fuel shocks is unclear. For example, It is reported that analysis by the Pentagon concluded that climate change's threat to global stability is far greater than that of terrorism (Homer-Dixon, 2006 p313). The geography of ownership and control of oil resources within a society will affect who and where would be affected (Bradshaw, 2010). The geopolitics of oil security will be influential. This is illustrated below: *"three of the major issues that now dominate the literature of global energy security: the US addiction to imported oil, the European Union's reliance on natural gas imports from Russia, and China's strategy of 'going out' to secure equity oil in Africa." (Bradshaw, 2009 p1920).* There are past examples of fuel disruptions in particular areas where the trigger cause is seen as geo-political events. Cuba experienced an extended period of fuel shortage due largely to the collapse of communism in the former USSR (Enoch et al., 2004). This in conjunction with their isolation by the USA led to a national level fuel shock. In Zimbabwe financial crisis and political instability led to reduced fuel availability. The Second World War has numerous examples of restricted access to fuels due to conflict (Gilbert and Perl, 2010).

Evidence based arguments have been made in the peer reviewed literature suggesting two opposing positions: One that there is not enough fossil fuel –

the Peak-oil argument. A second argument that there is too much fossil fuel available and this risks damage to planetary life support systems. Neither argument is conclusive. However if either position is correct then there is potential for fuel shocks This is summarised in Figure 2.1.

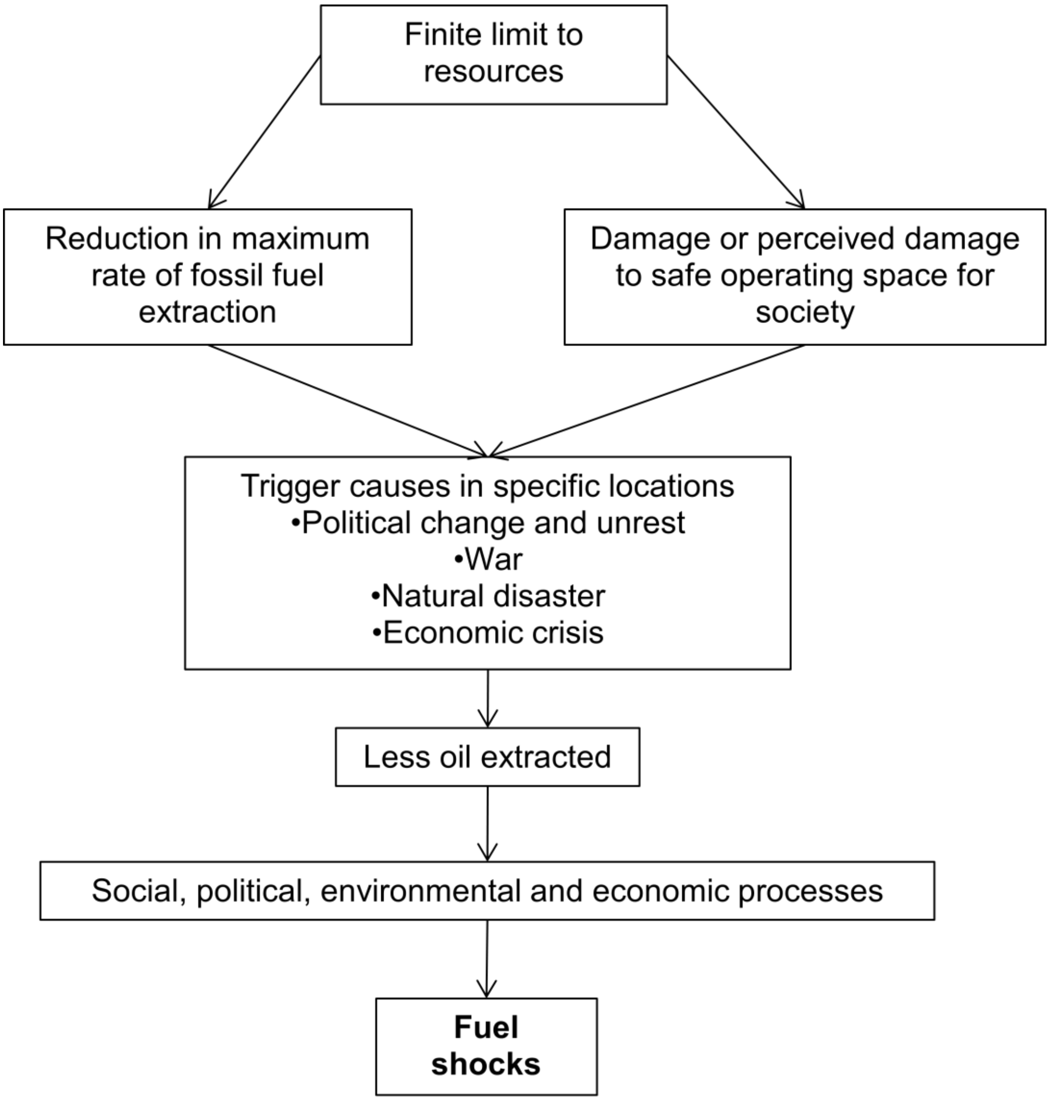

Figure 2.1: A summary of the root causes and trigger causes of fuel shocks based on analysis of the literature.

2.2.4 Scenarios offering a rationale for investigating fuel shocks

There have been a number of scenarios developed which argue that finite limits to resources and associated trigger causes make fuel shocks plausible events. They draw upon evidence including that considered in Sections 2.2.1-2.2.3 above. For example: Energy shocks are a feature of the UK Government Foresight scenarios (Curry, 2006). One of the Foresight scenarios is called *Tribal Trading* and contains the following features:

> "It is 2025. The energy shock has been sharper and more savage than anyone except the pessimists imagined."
> Government policy acts to restrict motorised travel.
> Local travel is typically by bike or by horse.
> BRIC nations such as Russia, who hold much of the remaining available oil, refuse to supply Western Europe seemingly turning off supply at the flick of a switch.
> The date Peak-oil occurs is assumed as 2011 after which negative effects of climate change are felt.

(After Curry 2006 p48)

There are similarities between the *Tribal Trading* scenario and the *Ecocommunalism* scenario developed by Gallopin, (2002) (Curry, 2006; Hopkins, 2010). They draw upon evidence that finite limits to resources have potential to negatively affect the transport system.

There are further more extreme scenarios based on collapse of society. For example *Overshoot* is a scenario where there is both consumption of resources way beyond long term carrying capacity and a lag time before effects are noticed. The outcome is that the dangers of overshoot are not anticipated or noticed and this leads to a shock event. This Overshoot scenario comes from the Beyond the Limits World3model (Meadows et al., 2004). A further example of an argument for collapse and rapid change is made by Diamond, (2006). His thesis is that there are examples of environmental factors being responsible for collapse of historical societies, and that current society shares features in common with the collapsed societies; thus arguing that current societies are at risk of severe change. Urry, (2010) also argues for the possibility of shocks. Urry argues that the current globalised economic system is consuming resources at a rate which endangers the continuation of that system, threatening possible collapse supporting arguments such as those made by Diamond, (2006). He questions the dominant economic and social models describing the current system. These models presume that if the current state of affairs is disrupted from its natural equilibrium, then it will return to its current state due to the effect of negative feedback mechanisms. He argues that these models are flawed, and that there is evidence that systems of planetary life support such as the climate system have in the past experienced abrupt changes. Further that the effects of a changing climate can have significant and sudden effects on regions or nations citing for example Homer-Dixon, (2006).

2.3 Resilience

- This section asks: What conceptualisations of resilience exist and could they express the concept of resilience to fuel shocks?

Dictionary definitions of resilience refer to withstanding difficult conditions (Soanes, 2003). This suggests that resilience might be a concept to examine fuel shocks. Resilience is a concept described in several disciplines including; resilience engineering as a means of managing safety and business processes (Hollnagel, 2006). In psychology resilience to events or stresses are examined (e.g. Rutter, 2010) and in child development examining positive adaptation despite adversity (such as Luthar et al. 2000). In computer science, research has been carried out on resilience of the internet to random breakdowns (Cohen et al. 2000). Resilience is also a commonly used term in disaster management (e.g. DfID, 2011; Klein et al., 2003). Within Geography and transport domains it is a term which has been used in transport economics (e.g Christopher and Peck, 2004), resilience of links and nodes within the network such as (Nicholson and Du, 1997; Sánchez-Silva et al., 2005) and transport security (Cox et al., 2011).

Resilience has multiple definitions and conceptualisations. There are three conceptualisations of the term resilience which may be relevant to transport fuel shocks: Engineering resilience, ecological resilience and evolutionary resilience. Some may be appropriate to representing fuel shocks whilst others may not. These are summarised in Table 2.1 and discussed in the following sections.

Table 2.1 Summary of three conceptualisations of resilience

Resilience concept	**Key features considered**	**Can it express the concept of resilience to fuel shocks?**
Engineering	resistance to disruption, and “Bouncebackability” - Return time to the current system state after a disruption.	No
Ecological	Resistance to disruption and return to current state after disruption. Also considers possibility of major system change from one regime to another if the disturbance is large enough. E.g. an ecosystem changes from savannah to desert with a major change in rainfall regime or a major increase in grazing. Because the system can change from one regime to another adaptation to the new regime is considered.	No
Evolutionary	Resistance to disruption. Return time to the current system state after a disruption. Major system change from one regime to another if the disturbance is large enough. Adaptation to a new regime following a large disturbance – apply existing adaptive capacity. Planned transition – attempting to build adaptive capacity in anticipation of a large disturbance which will cause change to the system. Planned radical transformation of the whole system from a vulnerable or undesirable regime to one which is less vulnerable and more desirable.	Yes

2.3.1 Engineering resilience

Engineering resilience is described as a reactive conceptualisation of resilience which attempts to maintain the current status quo and bounce back to what could be described as the current 'normal' or 'business as usual' (Manyena, 2006). The key features of engineering resilience are:

> *"[an] emphasis is on return time, "efficiency, constancy and predictability", all of which are sought-after qualities for a "fail-safe" engineering design(Holling, 1986) p. 31.*

Holling (1986) refers to engineering resilience as the traditional view of resilience which is consistent with concepts used in engineering and economics. Because engineering resilience is reactive, it does not have any means of expressing a major change from the current normal. The current normal in this case is a transport system with access to large amounts of fuel. A fuel shock would be a major departure from the current normal, so for that reason engineering resilience is not an appropriate conceptualisation of resilience to fuel shocks.

2.3.2 Ecological resilience

Ecological resilience, based on the work of (Holling, 1973), posits that systems can flip from one state to another given a large enough disturbance. Holling, (1973) explains that if pushed too far, instead of 'bouncing back', the whole system changes. Fuel shocks are an example of large disturbances – the whole transport system changes long term, from one with copious fuel to one with severely limited fuel. There are different dimensions of resilience depending on the size of disturbance and the response of the different elements in the system (Walker et al., 2004). One dimension is the ability to return to the current normal state by resisting the disturbance pushing the system towards a new state. The second dimension is adaptive capacity. This is the ability of system components to re-organise themselves and maintain essential functions after a disturbance which caused whole system change (Folke et al., 2010; Holling, 1986; Walker et al., 2004). Ecological resilience is still a reactive concept in that adaptive capacity is only considered in terms of individual elements reacting to change after that change has occurred. Policy may be applied reactively under this conceptualisation, but if policy is to be applied strategically it needs to deliver anticipatory action. Ecological resilience only allows reactive policy response to assist deployment of pre-existing adaptive capacity. For these reasons ecological resilience is not suited to conceptualising resilience to fuel shocks.

2.3.3 Evolutionary resilience

Evolutionary resilience draws on the resilience thinking framework (Folke et al., 2010) and critical social science to produce what is argued to be a conceptualisation of resilience appropriate for application in planning models (Davoudi et al., 2012). Evolutionary resilience considers other dimensions not considered by engineering and ecological resilience (Davoudi et al., 2012) and are described below.

2.3.3.1 Socio-ecological systems

Evolutionary resilience is a conceptualisation of resilience designed to incorporate all the elements of a socio-ecological system. A social ecological system is made up of several smaller interacting systems involving people interacting with each other, their physical surroundings and social structures such as culture. Definitions of SES include those by Berkes, (2003), Gallopín, (2006) and Glaser et al. (2008). The concept of SES acknowledges a finite limit to consumable resources and that depletion of a resource can force changes to systems. Additionally social-ecological systems are interdependent with the bio-physical systems which support human existence such as those described by Rockstrom et al., (2009).

2.3.3.2 Transformation and building adaptive capacity: consideration of anticipatory policy

People and policy making bodies could radically transform lifestyles and practices to increase resilience. A vulnerable transport system dependent upon fossil fuels could be radically transformed to one based on walking and cycling in urban areas designed for low travel distance demand, thus making the transport system more resilient to fuel shocks. Another form of anticipatory action is building adaptive capacity. Building adaptive capacity does not necessarily involve radical change to mode share or complete reconstruction of urban areas prior to a shock. It involves helping people to prepare for a fuel shock, for example by making it easier to make journeys by bike[6]. Note how this differs from ecological resilience. Here steps can be taken to increase adaptive capacity before a shock occurs whereas ecological resilience only considers adaptive capacity post shock. Radical transformation and building adaptive capacity are described as forms of active transformation by (Folke et al., 2010). Evolutionary resilience

[6] Note making it easier to travel by bike does not necessarily mean altering behaviour in terms of increasing mode share prior to a fuel shock.

considers intentional human actions (Davoudi et al., 2012), which anticipate fuel shocks and act before they occur whereas engineering and ecological resilience do not. The need for policy and planning tools which consider breaks with current trends has been identified by Banister and Hickman, (2013).

2.3.3.3 Caveats to make explicit when applying evolutionary resilience

Davoudi et al., (2012) argue that in addition to the dimensions of evolutionary resilience which cannot be expressed by engineering and ecological resilience described above, there are caveats to applying evolutionary resilience to policy models which should be made explicit in the scope or simplifying assumptions so that users are clear what is being considered. These caveats relate to specified resilience. Here they are interpreted in the context of resilience to fuel shocks.

2.3.3.4 Specified resilience

(Carpenter et al., 2001) argued that to gauge resilience it has to be specific to a problem or scenario. Specified resilience (Carpenter et al., 2001) is defined as the resilience of one thing to another. Specified resilience is common to all three conceptualisations of resilience, but with evolutionary resilience the question is asked explicitly: what should be resilient? Deciding what has to be resilient determines the range and type of policies which could be considered (Pendall et al., 2009). Specifying resilience too narrowly reduces the range of response (see Table 2.2).

Reliance on purely technological responses may lead to further problems (Beck, 1992; Giddens, 1999) or the technological fix may not be practicable in the time available. Both of these outcomes are not resilient. Considering only the resilience of engineered systems may also exclude the resilience of people or communities (Davoudi et al., 2012; Folke et al., 2010). Marsden et al., (2014) argue it is important to consider both the transport infrastructure and the activity system of people in developing resilience and adaptation policies for transport planning.

Table 2.2 The scope of resilience affects the range of policy responses

Resilience of what	**To What**	**Range of responses**
Resilience of activities: people's ability to make journeys such as the journey to work	Fuel shocks	High: Social change Technological change E.g. mode change, redesign of urban environments, change of economic system
Resilience of current travel time by car	Fuel shocks	Low: Reliance on technological change E.g. Build coal fired power stations to power an electrified car fleet

If the resilience of people is considered then evolutionary resilience makes explicit that individuals are not all the same – not all people possess the same level of resilience and that policy and planning models have to be aware of this. There is a danger that resilience of people could be interpreted as self-reliance of people (Davoudi et al., 2012). This can occur if the ecological metaphor of resilience is used; it creates a danger of the notion of 'survival of the fittest' being invoked.   This leads to the assumption that the level of resilience people possess is just the natural way of things; so therefore outside of the scope of policy. This is used as a further argument against using ecological resilience in planning and policy making.

2.4 Conclusion

There is evidence that fuel shocks could occur. Finite limits to resources could cause fuel shocks which are triggered by other events which have been known to cause fuel supply disruptions. Evolutionary resilience could express resilience to transport fuel shocks.

3 Transport planning and indicators of adaptive capacity

This chapter forms the second part of the literature review. The previous chapter established firstly the potential for fuel shocks resulting from finite limits to resources. Secondly it established that the evolutionary conceptualisation of resilience could express resilience to transport fuel shocks. The next step in reviewing existing literature is to examine transport planning and indicators of adaptive capacity. Section 3.1 reviews current consideration of fuel shocks, resilience and resilience to fuel shocks in transport planning including an assessment of whether there are currently any suitable indicators which could be used to assess resilience to fuel shocks. Section 3.2 examines how transport planning decisions are made, giving an overview of the current transport planning decision making framework. Planning goals and appraisal are discussed. These mechanisms rely upon indicators. Indicators are discussed in terms of their function and how to determine their quality. Section 3.3 summarises the findings of chapters 2 and 3.

3.1 Current consideration of fuel shocks, resilience and resilience to fuel shocks in transport planning

This section reviews current consideration of fuel shocks, resilience and resilience to fuel shocks in transport planning including an assessment of whether there are currently any suitable indicators which could be used to assess resilience to fuel shocks. It asks the question: What is currently being done to consider fuel shocks in transport planning? Fuel shocks are not directly considered by the UK government. Specific guidance is offered by the UK government to businesses to help them prepare for fuel supply disruptions lasting between 2 and 10 days (Cabinet Office, 2011) though not fuel shocks. The UK does have legislation in place called NEP-F (National Emergency Plan-Fuel) to allocate fuel to emergency services and essential functions for public safety, well being and upholding the rule of law and democratic process (Cabinet Office, 2011). This is designed for use in the event of a fuel supply disruption in times of natural disaster, economic or political crisis; though it could be applied as the trigger of a fuel shock.

Climate change is a possible cause of fuel shocks as discussed in Section 2.2.2. The UK's key climate change policies are built around the Climate

Change Act 2008 which has a target of 80% reduction in CO_2 emissions by 2050. The UK government has produced a climate change risk assessment covering transport. Fuel supply disruption (short term disruption) is noted as a risk, but the key transport risks are disruption due to flooding and flood damage to infrastructure (DEFRA, 2012), not fuel shocks. The transport white paper of 2011 does not make reference to fuel shocks (DfT, 2011a). Its title states its focus as being “creating growth and cutting carbon”. The greatest opportunity for cutting carbon, it states, is by encouraging car journeys under 5 miles to be changed to other modes. The UK government commitment to reducing carbon emissions has been questioned by the media by Mason, (2013) and in academic literature specifically looking at transport emission reduction by Aldred, (2014a) who argues that whilst mode change of short personal journeys is helpful, other changes such as tackling aviation emissions and long distance freight which would also create significant reductions in carbon emissions are not tackled for political reasons.

Another possible cause of fuel shocks is Peak-oil, but this does not appear to be considered in UK policy. A UK government report based on work carried out in 2007, concluded that the time scale and the impacts of Peak-oil were too uncertain to justify any policy measures not already considered within the policies for climate change mitigation and adaption policies, which they argue encourage movement towards a low carbon economy (DECC, 2009). Additionally the transport white paper of 2011 does not make reference to Peak-oil (DfT, 2011a). The evidence above shows fuel shocks are not considered directly; only short term fuel supply disruptions. Of the root causes of fuel shocks identified in Section 2.2, Peak-oil is not considered and the consideration of climate change is stated but the level of commitment is questioned.

3.2 What is currently being done within transport planning to consider resilience?

The scope of a UK government call for a review of transport resilience (DfT, 2014a) is shown in Table 3.1. Resilience to fuel shocks is not directly considered. The specified resilience focuses on large scale infrastructure to short term disruptions. The focus on resilience of infrastructure is narrow and based on engineering resilience concepts. With this focus and conceptualisation, it may fail to consider resilience of people’s ability to take part in activities or make journeys.

Table 3.1 Scope of UK transport resilience review after (DfT, 2014p2).

Note there is no direct consideration of walking and cycling, and no consideration of fuel shocks

The review will examine:

- plans to mitigate impacts from severe weather events
- contingency planning to manage the effects of severe weather
- investigation of increased rates of asset degradation and the effects on asset performance and service life
- adaptation of infrastructure to manage projected future risks

- It will also consider the following parts of the transport industry:
- the strategic road network and local roads
- the national rail network, including private and public transport
- aviation - airports of economic and strategic importance
- maritime - ports of economic and strategic importance
- light rail and underground systems

The UK National Adaptation Plan (NAP) is based on adaptation to climate change (DEFRA, 2013). The specified resilience is again narrow, based on resilience of infrastructure to natural hazards such as flooding: *"An infrastructure network that is resilient to today's natural hazards and prepared for the future changing climate." (DEFRA, 2013 p.30)*. The NAP does consider resilience but not resilience to fuel shocks.

In addition to the NAP and the transport resilience review, the UK government has published a framework for community resilience (Cabinet Office, 2011). Their definition of community resilience is based on harnessing local resources to compliment the emergency services to aid recovery after emergencies. This is an engineering resilience conceptualisation, which as shown in Section 2.3.3, is not compatible with fuel shocks. The framework for community resilience is part of a suite of policy documents from the National Security Strategy and Strategic Defence and Security Review (Cabinet Office, 2011), so it is broadly related to threats to security. Much resilience planning in the past decade has been related to securitization, and the term 'community resilience' is strongly linked to counter-terrorism (Coaffee and Rogers, 2008). Interestingly, the Cabinet Office Community Resilience Framework refers to the work of the Transition

Towns Movement[7] though only to infer that it is beyond the scope of the framework and therefore not considered. The Transition Towns movement believes there is potential for fuel shocks as a result of the interaction between Peak-oil and climate change (Hopkins, 2008; Hopkins and Lipman, 2008).

Currently the UK government uses an engineering conceptualisation of resilience. From the literature reviewed in Section 2.3.3, it was established that an evolutionary resilience is a more appropriate conceptualisation to assess resilience of the transport system to fuel shocks. Criticisms of using engineering focussed resilience can be found in Davoudi et al., (2012); Frerks et al., (2011); MacKinnon and Derickson, (2012); Pendall et al., (2009); Swanstrom, (2008). Such criticism suggests little hope for getting evolutionary resilience to fuel shocks being considered by the UK government and governments of other similarly developed nations. The reasons fuel shocks are not currently being considered are at least in part due to the political ideology of the government – resilience is a political issue (Prior and Hagmann, 2013). This is not to suggest that things cannot be changed. A more optimistic view is held by Adger (in Hopkins, 2010), who is broadly optimistic. Even though the current engineering resilience is focussed on security and emergency planning, it does show an opening for debate on broadening the conceptualisation of resilience leading to consideration of shocks.

Aside from the political dimension there may also be practical reasons why resilience of the transport system to fuel shocks is not currently considered. It may be related to lack of information to inform policy. The quote below is illustrative:

> *"much reference was made to the 'data gap' (in relation to cycling, but it's not only cycling that's affected). We don't have the data, so we can't put it into the model, so we don't know what will happen, so we can't plan for it, so very few people do it, so there's no policy interest – and no data. Nicely circular…. But the right data, at the right time, can help bring about change " (Aldred, 2014b)*

To investigate this idea the next section examines literature which suggests a data gap is a barrier preventing resilience to fuel shocks being considered in transport policy and planning.

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[7] http://www.transitionnetwork.org/

3.2.1 Resilience to fuel shocks in transport planning – Are there current indicators of adaptive capacity?

This section asks: Is there a measure of adaptive capacity available which captures resilience of transport to fuel shocks focussed on the contribution which can be made by walking and cycling? To recap, adaptive capacity is one form of resilience. Having the capacity to walk or cycle to work following a fuel shock, is a form of adaptive capacity. Indicators are easily understood measurements which describe the state of a system (Mitchell et al., 1995). A more detailed discussion of indicators and their role within transport decision making is found in Section 3.3.3

There is literature which could be used to derive indicators of adaptive capacity in terms of changing the built environment. Following a fuel shock the only modes of transport available would be walking and cycling. This makes active modes key to adaptive capacity following fuel shocks. The built environment affects the propensity to walk and cycle. There is a considerable literature on this topic (for example see Cervero, 1997; Saelens and Handy, 2008; Parkin, 2004). Propensity to walk and cycle is affected by the capacity to walk and cycle. Literature from this field may provide useful indicators of adaptive capacity in terms of changing the built environment along with literature on larger scale urban morphology and land use e.g. (Cervero et al., 2002; Bertolini et al., 2005; Cheng et al., 2007). Increasing resilience by transformation and increasing adaptive capacity to fuel shocks by changing the built environment would be a long term and very high cost process (Ferrary et al., 2011). Also, being infrastructure focussed it may not consider people’s ability to participate in activities which Marsden et al., (2014) argue is important to consider in developing resilience and adaptation policies for transport planning.

Small scale adaptive capacity considers people’s ability to participate in activities following a fuel shock. Small scale adaptive capacity is a focus on adaptive capacity of individuals in small geographies sensitive to a variety of policy measures, such as those affecting fitness, obesity, bicycle availability and bicycle infrastructure, whose impacts (at least in the short term) are on a smaller scale than large-scale land use and urban morphology change. Small scale adaptive capacity could be increased over a shorter time scale than built environment change with lower costs of policies that transform or increase adaptive capacity. Current walking and cycling mode share does not indicate capacity for people to use active modes post shock. Models of propensity to cycle to work have been developed (e.g.Parkin, 2004) which accounts for current attitudes and behaviours and choices. However, current attitudes, behaviours and choices do not determine capacity to cycle (or walk) to work after a shock. If walking and cycling become the principal transport modes after a fuel shock, then physical fitness is a factor of adaptive capacity. Indicators do exist to assess effects of policies on physical fitness and are in use in UK transport planning (DfT, 2007). A measure of physical fitness alone cannot give a measure of adaptive capacity.

It would appear from the literature that other countries do not have indicators to explicitly examine resilience. For example Mihyeon-Jeon and Amekudzi, (2005) give examples of indicator sets used in economically developed nations and international bodies and Miranda and Rodrigues da Silva, (2012) in Brazil. The indicator sets examined do not collect the range of information which would be needed to give a measure of adaptive capacity to transport fuel shocks. For example they do not collect the fine grained information about people's capacity to travel by bicycle such as ownership at small geographies and individuals' ability to propel a bicycle.

Proposed indicator sets for sustainable urban mobility, such as those suggested by Litman and Burwell (2006) or Toth-Szabo and Várhelyi, (2012) include some indicators which measure some factors of adaptive capacity but it is not considered explicitly. For example Marletto and Mameli, (2012) consider walkability and cyclability as measures of the propensity to use active modes under current conditions. Accessibility statistics and indicators use assumptions about trip length by active modes based upon current circumstances and behavioural preferences. For example, The UK accessibility statistics travel time calculation methodology assumes that cyclists will travel at 9.9 miles per hour (16km/hr) (DfT, 2012), and trip durations are based on current estimates taken from the UK National Travel Survey. Forester, (1983) assumed that 5miles (8km) is a distance which a cyclist could travel in many urban areas. Anecdotal evidence in the form of discussions with transport planners is that drawing a 5mile circle around a development determines its accessibility by bicycle. These measures do not give an adequate measure of adaptive capacity after a shock. They do not even account for capacity related determinants of propensity to cycle under current conditions such as hilliness, modelled for example by Parkin, (2004). Parkin, (2008) argued that physical effort does not receive sufficient attention when modelling bicycle journeys. None of the statements above take account of variation in physical effort.

Socially contextualised indicators of vulnerability to fuel price increase have been developed which seem related to resilience to fuel shocks. Dodson and Sipe, (2007) suggest an indicator of vulnerability of the populations of different areas to fuel price rises in Australian cities. It identifies areas which may have to change if there are price rises. It does not measure the capacity of the individuals there to adapt. A similar concept has been applied in the UK by Lovelace and Philips, (2014). They discuss several metrics including *commuter fuel poverty* an indicator developed by Lovelace and Ballas, (2012). However these are indicators of vulnerability to fuel price increase – not a measure of adaptive capacity, resilience or any form of coping strategy in the event of a fuel shock. Indeed it suggests investigating the capacity to continue to make journeys after a fuel shock as an area for further work.

Rendall et al., (2011) provide an indicator which can be consistent with the definition of evolutionary resilience described in Section 2.3.3. They define active mode accessibility (AMA) as *"the proportion of activities that can be reached by active modes alone, given the population demographics of the study area" Rendall et al., (2011 p72)*. They continue, stating that AMA is a "*behaviour –independent property of the built urban form" Rendall et al., (2011 p74)*. They assume that the nearest service can provide the desired activity. This may not always be the case; schools may already be at capacity and nearby work places might not provide jobs that the local population are skilled for. They use the notion of active mode accessibility to suggest changes to urban morphology and land-use to increase adaptive capacity in the event of a reduced supply of fuel due to Peak-oil. The mitigation strategies considered are changes to land-use which are as discussed above large scale long term changes. These are useful strategies to be implemented in anticipation of a shock. Other land use and transport interaction models would also be suitable for examining large scale mitigation strategies. However there are also non land-use "small scale" factors which influence the ability of individuals to adapt after a shock. Small scale indicators could be a useful complement to existing indicators. The land-use focussed indicators described above are too high level to examine localised, individual and community oriented policy interventions. It would not pick up the effects of policy interventions aimed at changing obesity or bike availability on adaptive capacity. The land-use focussed indicators capture some aspects of adaptive capacity, but there is currently no indicator which shows adaptive capacity of people to transport fuel shocks, which would be sensitive to policy interventions at the small scale of interest. A complimentary indicator is required which identifies further aspects of people's ability to participate in activities post fuel shock.

3.3 How are transport planning decisions made? The current transport planning decision making framework

A transport planning framework is a decision making mechanism (Headicar, 2009; VanWee et al., 2013). Marsden, (2008 p1) introduces MSc transport planning students to the concept of transport planning as follows:

> *"Meyer and Miller, (2001) define it "at its simplest level" as the process of answering four basic questions:*
>
> *Where are we now (such as trends and conditions relating to population, the transportation system, and the general state of the urban area)?*
>
> *Where do we want to go (major issues, public outreach results, obstacles and opportunities)?*
>
> *What will guide us (mission statement, goals, objectives, public input, and performance measures)?*
>
> *How will we get there (revenue estimation, project and program implementation, public/private partnerships, and policy changes)?"*

This type of approach is called objectives led transport planning. Variations on this approach are common in developed nations such as the UK (May, 1996). These have the following stages:

- Set objectives / based on an understanding of overall vision and problems to be addressed
- Determine strategy
- Appraisal of alternatives
- Implement policy
- Evaluation of outcomes

3.3.1 Goals and objectives in transport planning

Transport policy makers and planners have high level goals sometimes referred to as an aim or vision. For example this is the overall aim of the transport plan in West Yorkshire UK:

> *"To develop and maintain an integrated transport system that supports economic growth in a safe and sustainable way and enhances the overall quality of life for the people of West Yorkshire" (WYLTP, 2006, p10)*

Specific objectives direct progress towards the overall goal. A goal could be established to increase resilience to fuel shocks. At this level then it appears the existing transport planning framework could address the problem of fuel shocks.

Economic growth dominates transport policy objectives (Banister and Berechman, 2001; DfT, 2011a, 2009a). Other objectives such as environment, accessibility and equity are stated as important in planning and appraisal documentation (DfT, 2007), but it is argued that they need to be given higher priority in practice (e.g Banister, 2008; Lucas, 2012). A goal to increase resilience to fuel shocks using an evolutionary conceptualisation of resilience would contribute to access, equity and environmental sustainability objectives. However engineering resilience would be very narrowly defined and in practice is likely to focus on the “bounce- back” of the economy.

3.3.2 Appraisal

The transport planning framework involves some system of appraising potential options. In the UK and other countries, there is an attempt to have some form of objective assessment, which gathers data and estimates the benefits and dis-benefits of a policy action. Two definitions of appraisal are given below:

> *“Appraisal is the process of assessing the worth of a course of action – which includes projects, programmes or policies. Evaluation is similar to appraisal, although it uses historic data and takes place after the event.”* (DfT, 2005)

> *"A set of interrelated expenditures, actions and policies designed to achieve a country’s specific objectives for economic and social development within a specific time scale".(Adler, 1987)*

3.3.2.1 Appraisal by Cost Benefit Analysis (CBA)

There are two broad types of appraisal; Cost Benefit Analysis (CBA) and Multi Criteria Analysis (MCA) approaches. There are also hybrids which include aspects of both approaches.

CBA is the most common form of appraisal in the EU (Odgaard et al., 2005). CBA is an economic tool. Its main feature is the search for economic efficiency. That is, achieving the maximum value in terms of investment made in projects. “The transport planning process is driven by the desire to reduce time and cost” (Banister, 1994p221). Travel time savings are given an economic value, and this theoretically reduces the costs of a person’s journey and benefits the economy as a whole. Focus on travel time savings appears to still be the highest priority in the UK where the emphasis is on “growth and carbon” (DfT, 2011a). Social Cost Benefit Analysis (SCBA) aims to go beyond purely “business case” of CBA and aims to “derive a summary indicator of the costs and benefits for all the actors involved” (VanWee et al., 2013p330). SCBA is the form of cost benefit analysis generally is used in governmental policy analyses.

3.3.2.2 Conceptual or high level issues with CBA

There are some high level issues with current applications of CBA frameworks pertinent to assessing the impacts of fuel shocks. CBA is an economic tool. This is an issue firstly because a fuel shock is an example of a problem caused by finite limits to resources. Classical economic approaches upon which CBA is based assume that if one resource becomes scarce it can be substituted for another. Substitution ignores finite resource limits (Daly, 1994). Related to the problem of substitution is trade off. Trade off of environment and social factors against economic ones is assumed in CBA. This may not be appropriate. CBA is a compensatory analysis – a good economic score compensates for poor environmental or social scores. A simple CBA examines cost of project versus travel time savings as highlighted by (Banister, 1994). Policy appraisal involving non-motorised transport and accessibility involves *non-monetized goods* (Litman, 2013). A fuel shock could dramatically reduce ability to participate in activities. This is a more fundamental concern than cost and time savings. Economic tools including CBA have been criticised for failing to take account of the distributional and equity aspects of transport policies (Lucas and Jones, 2012). CBA discounts for time – this has the effect of under valuing future impacts such as a fuel shock. Fuel shocks would result in some people being unable to participate. This is different to the notion of changing behaviour to a lower cost alternative. *“Standard cost benefit analysis is not the proper instrument in this case because it measures overall economic efficiency rather than the equity concerns of certain disadvantaged groups” (VanWee et al., 2013 p335).* Methods such as Multi Criteria Analysis (MCA) may be more suitable tools. (VanWee et al., 2013).

3.3.2.3 Appraisal by Multi Criteria Analysis: An alternative appraisal framework to CBA.

Multi Criteria Analysis (MCA) is an alternative appraisal method to address the problem of including *non-monetized goods*. Rather than seeking ways of monetizing all factors as above, all factors considered in the appraisal are given a weighting (Nijkamp, 1990). Multi criteria analysis involves collecting data (either quantitative or qualitative) about all important factors relating to a policy decision. The relative importance of each factor is determined by giving it a weight. The relative merits of different policies can then be evaluated. Factors connected to fuel shocks which might not be picked up in CBA could be included in an MCA. The UK uses a system which involves some monetized elements assessed as per a CBA, and other elements assessed with other indicators (DfT, 2007). The overall result of the appraisal depends upon the weights given to the different elements. In recent times there has been a debate on the relative merits of using CBA and MCA individually or combining these approaches (Browne and Ryan, 2011; Gasparatos et al., 2008; van Wee, 2012).

In terms of assessing resilience to fuel shocks there may be high level issues. The decision as to whether to include resilience to fuel shocks in the MCA is not automatic. It may not be included. If included, weightings may be given which give it little importance. Gühnemann et al., (2012) point out that MCA like CBA tends to be compensatory. As explained above, this means that if a scheme has a poor environmental score then it can be compensated for by a good economic score. Banister et al., (2012) note that the current transport planning framework, its organisational and institutional structures are concerned principally with economic growth and not with ensuring transport systems avoid excessive depletion of the finite resources which could be the root causes of fuel shocks. Because of this they argue that current transport planning frameworks may not be capable of addressing the issues of climate change and transport. This may then also be the case with fuel shocks and transport. There is argument for changes of conceptualisations of resilience and adaptation used in transport planning (e.g Banister et al., 2012 and Marsden et al., 2014). These arguments may be bolstered by data and indicators which plug the 'data gap'.

3.3.3 Indicators in transport policy

If Multi Criteria Analysis (MCA) based appraisal is carried out then variables other than monetized goods are considered. These variables are called indicators. Indicators have been defined as:

> *"Indicators are used to interpret the world about us. Indicators convey information on complex systems in a way that makes those systems more easily understood… Indicators are alternative measures that are used to identify the status of a concern when for technical or financial reasons the concern cannot be measured directly… They do this by:*
>
> *(1) Synthesizing masses of data; (2) Showing the current position, in relation to desirable states;*

> *(3) Demonstrating progress towards goals and objectives; and*
>
> *(4) Communicating current status to users (scientists, policy makers or the public) so that effective management decisions can be taken that lead us towards objectives." (Mitchell et al., 1995)p105*

The indicators may be quantified or quantitative but are converted in to numerical or ranked values before use in a MCA.

3.3.3.1 Indicator functions

Indicators exist within a context of governance. The decision on whether an indicator will be used in policy making is subject to social and political influence. For example one political group may reject the use of an indicator for purely ideological reasons, another may reconsider its position on an issue when presented with evidence from an indicator. This is an idea from Pastille Consortium, (2002). They suggest that the uses of indicators can be grouped based on a political science approach such as that of Boulanger, (2007). Boulanger gives a political science based classification of indicator use. There are two useful groups; a "Rational – positivist" set of functions and a "Discursive – constructivist" set of functions. The former is associated with objective description and assessment of phenomena which allows it to be used as a measurement tool. The latter are the functions of indicators which allow them to frame problems in discussions. Table 3.2 summarises indicator functions. Pastille Consortium, (2002) assert that it is important that both these groups of functions be considered when trying to produce effective sustainability indicators.

Quantifiable indicators are more common. In a review of definitions of indicators, quantifiability and measurability were key features (Gudmundsson, 2010). For example Marsden and Bonsall, (2006) explain the development of a culture within the UK public sector which relies upon performance targets measured by indicators. They note that issues which are not covered by indicators and targets are ignored or sidelined. In a UK context indicators which can be used as objective, robust, quantifiable, statistically sound tools are more likely to gain entry into the policy debate. These are all statements which are associated with quantitative measures. It shows that quantitative measures are preferable in UK policy making (Marsden, 2008b). Litman, (2007) appears to echo this internationally. A list of indicators of sustainable transport in Mihyeon Jeon and Amekudzi, (2005) covering economically developed nations and international bodies also showed quantitative indicators dominate.

Table 3.2: Indicator functions after (Gudmundsson, 2010, Boulanger, 2007)

*Learning will contribute to understanding the functioning of systems.

Boulanger's groups of functions	**Indicator functions**
1. A "Rational – positivist" set of functions. Objective measures of phenomena, a technical tool.	Describing the situation– What is going on? Assessment - How are we doing? Prioritizing and deciding – What should we do? *
2. A "Discursive – constructivist" set of functions. Framing problems, encouraging discussion of issues.	Focus the attention – discuss what is important? Accountability function – Discussion of change to accountability functions to emphasize what is important. Prioritizing and deciding – What should we do? Communicating - how do we tell others? *

3.3.3.2 Assessment of indicator quality

Indicators have to be 'good' in terms of their "Rational- positivist" functions in order for them to be accepted as decision making tools. As explained above, they can also have a discursive function to develop a discussion of issues which should be considered but currently are not. If the methods used to develop an indicator are sound, it increases the credibility of the indicator (Mitchell et al., 1995). Marsden et al., (2006) summarise features of good indicators which could be used as criteria for inclusion in Table 3.3. Though it is not explicitly mentioned, it is inferred in Table 3.3 that indicators should be transparent. It should be clear what data is used, how it is used and the method to calculate the indicator value should be open. Methods should be open so that any assumptions can be made clear and results can be reproduced.

Table 3.3 Characteristics of good indicators (after Marsden et al 2006)

Good indicators are: • Useful – have clear functions • Clearly defined – no ambiguous terms • Non-corruptible – no way of twisting reporting of data to suggest more positive values • Controllable – reflecting transport's contribution to wider issues • Measurable • Responsive - able to show change over a specified time period or at a particular spatial resolution. They must also be sensitive to policy measures • Easy to understand – by practitioners, politicians and general public – relevant to experience • Cost effective to produce

3.3.3.3 An example: The UK transport planning framework

Table 3.4 The objectives of the NATA transport appraisal framework. Source: (DfT, 2014b P5)

Environmental impact involves reducing the direct and indirect impacts of transport facilities on the environment of both users and non-users. There are 10 sub-objectives including noise, atmospheric pollution of differing kinds, impacts on countryside, wildlife, ancient monuments and historic buildings. **Safety** is concerned with reducing the loss of life, injuries and damage to property resulting from transport incidents and crime. The 2 sub objectives are to reduce accidents and improve security. **Economy** is concerned with improving the economic efficiency of transport. The 5 sub-objectives are to improve economic efficiency for consumers and for business users and providers of transport, to improve reliability and the wider economic impacts, and to get good value for money in relation to impacts on public accounts. **Accessibility** is concerned with the ability with which people can reach different locations and facilities by different modes. **Integration** aims to ensure that all decisions are taken in the context of the Government's integrated transport policy.

The UK transport planning framework is based on a process called NATA (New Approach to Transport Appraisal) developed following the 1998 transport white paper (DfT, 1998; Headicar, 2009). It broadly follows the stages above. NATA has five objectives. These are shown in Table 3.4.

3.4 Conclusion

From the literature review it could be inferred that: Transport fuel shocks are important so shouldn't policy makers know who could get to work by walking and cycling if there was no fuel for motorised transport? There is evidence that transport fuel shocks are possible. Though it is beyond the scope of this thesis to predict the consequences of fuel shocks it is obvious that there would be both economic and social consequences if there is neither resilience as a result of radical transformation nor adaptive capacity built by anticipatory policy intervention prior to a fuel shock. This literature review has shown that evolutionary resilience is a concept which can be used to describe fuel shocks and policy responses to them. Fuel shocks are not considered in UK planning. Resilience is considered in UK planning, but not in the context of fuel shocks. There is a political gap to implementing policies to increase resilience to fuel shocks, as well as a data gap. The literature reviewed suggests that progress towards bridging both of these gaps can be made by developing a good indicator of adaptive capacity to fuel shocks; one with *Rational- positivist* functions in order for it to be accepted as robust enough to be used as a decision making tool and also a *discursive function* which can easily communicate the importance of resilience to fuel shocks and be capable of influencing the policy debate (or being used by those who wish to influence the policy debate).

Section 3.2.3 shows indicators are important means to represent issues in transport policy. This justifies a need for indicators of resilience to fuel shocks and the subset I am interested in – adaptive capacity indicators of "small" scale factors; that is those not involving large scale land-use and urban morphology change which influences individuals in small geographies. Section 3.1.3 demonstrates a lack of suitable indicators which justifies the production of a new indicator. This requires development of a method of calculation because appraisal methods and indicators in transport planning are primarily quantitative.

4 Indicator design

4.1 Introduction

Chapter 4 details the scope of the indicator which was outlined in Section 1.4 and based on this presents a conceptual indicator design. The indicator scope is based on the pre-requisites for indicators in transport policy discussed in Section 3.3.3 A diagrammatic representation is made of the factors which influence the indicator. There is also an explanation of the determinants of resilience to fuel shocks. Chapter 4 contributes to objective 1:

> To develop a generic approach to estimating indicators of resilience to transport fuel shocks.

Section 4.2 defines the indicator scope and 4.3 the indicator design.

4.2 Scope

The approach of the work is to develop an indicator of adaptive capacity to fuel shocks. Indicators help provide understanding of a situation of interest (as discussed in Section 3.3.3). Indicators are not themselves predictive. The situation of interest may be based on either: the present time using current data, a scenario or a predictive model of the future. Before indicators are calculated, a separate process is required to define the situation of interest. The outputs of this process are used as inputs to the indicator calculation process. This is a fairly simple idea, commonly found in transport planning. In this thesis the situation of interest is defined initially by a simple scenario in which a fuel shock occurs today and adaptive capacity is estimated immediately after the shock.

The situation of interest in this thesis is a simple scenario; a fuel shock which occurs today. The reasons for this are: Even though this situation is unlikely it is of policy interest. Chapter 2 established that fuel shocks are a sufficient threat to be taken seriously in transport planning. Imagining major forced changes aids consideration of major changes in policy direction (Banister and Hickman, 2013). Secondly, if the scenario assumes a fuel shock occurs today current data may be used. Using current data means that there is no need for a predictive model of the future to define the situation of interest and consequently no need to speculate about the attributes of individuals at the time of the shock. Thirdly, an indicator based on this simple scenario, results in a base case indicator, which can be compared to counter factual policy case in the same scenario. It could also be compared to indicators based on a different situation of interest produced in future work.

If the indicator were to be constructed based on a situation of interest that does not use current data, then a predictive model would be required. A predictive model of the future would require consideration of human behaviour. As a predictive model is not necessary, human behaviour is not considered. The indicator calculation methodology can use the outputs from any situation of interest deemed to be of policy interest. It is important to reiterate that a predictive model is not needed in this thesis so is not used. However, objective 1 is to develop a generic approach to estimating resilience to transport fuel shocks. Therefore it is worth considering briefly some of the issues of using a predictive model should they be needed in future work.

The challenges of building a model which predicts how people’s attributes change between now and a fuel shock at a point in the future would include accounting for the effects of human behaviour. There would be uncertainty in this predictive model. Firstly there is no empirical evidence as to how people in the UK behave in the lead up to a fuel shock because there has never been one before. Different behavioural responses are possible, for example, if a shock were anticipated; behaviour may be different to if the shock were not anticipated. Speculation would be required to estimate the assumed level of anticipatory response. This could greatly affect the predicted attributes of individuals which would in turn greatly affect the indicator value. Speculation about future human behaviour has the potential to undermine the quality of the indicator. The definition of the situation of interest could be manipulated by specific interest groups. The data derived from the manipulated situation of interest would then produce a corrupted indicator value. Non-corruptability is a feature of good indicators as defined in Table 3.3 (Marsden et al., 2006). To avoid this problem either evidence would have to be produced justifying a particular predicted behavioural response, or a set of indicators produced for a range of scenarios which take account of the range of uncertainty in future human behaviour. Addressing the challenges of building a predictive model which considers human behaviour is not necessary to achieve the aim of this thesis.

To avoid speculation about the post-shock situation, I choose to concentrate on a hypothetical situation on the first day after a sudden shock, i.e. before society has had any opportunity to make a post-shock adaptation. It is possible to offer evidence from current data to suggest adaptive capacity at this point. However, if the measure is calculated some weeks or longer after the shock, there is no evidence of how people may change. Many forms of adaptive capacity are not possible immediately following a fuel shock. The indicator considers one aspect of adaptive capacity: Attempting a comprehensive assessment of every different form of adaptive capacity would have been less useful as an indicator. In practical terms, attempting to measure every facet of resilience would be complex, require a great deal of data, require speculation about post-shock human behaviour, be impractical to calculate for many areas and outputs may be so complex so as to not offer practical help to decision makers. It is important to state that the guiding approach of this work is to produce an indicator of capacity to adapt immediately after a shock rather than a prediction of post-shock behaviour. The policy value of calculating capacity is that it describes an upper bound of what might be possible. Capacity measurement on its own is perfectly valid as an output. Indicators and proxies of capacity are common in science, decision making and policy. The decision to estimate *adaptive capacity* rather than *behaviour* immediately after a shock also avoids the need for speculation about attitude and behaviour change (or not) resulting from shocks.

I hypothesise that the adaptive capacity the morning after the shock at a local scale will affect longer-term and larger scale adaptive capacity and overall resilience. Thus, while *predicting* the longer-term adaptive capacity is beyond the scope of the work, I believe the calculated measure to be a useful indicator for both the shorter and longer term.

I will investigate the ability of people to continue making the journey to work. This is clearly a rather artificial situation but it captures a key aspect of resilience of the present transport system, and the journey to work is a journey type that is easy to understand. The guiding approach throughout involves making maximal use of pooling existing data sources, one might call it an 'empirically-grounded indicator', which will lead to ease and cost effectiveness of the production of an indicator for a wide variety of areas. The purpose of the indicator is to assist in decision making by firstly assessing the effect that specific policy interventions would have on adaptive capacity to fuel shocks, and secondly by fulfilling discursive functions. A good indicator (see Table 3.2) capable of performing its Rational-positivist functions may then be accepted into the governance debate as explained in Section 3.2.3.1.

4.2.1 Indicator scope specific points

The indicator should provide a quantified description of the spatial impacts of policy. The indicator should show variation between:

1. Base case and specific policy interventions
2. Small areas in the base case
3. Small areas when specific policies are applied.

4.2.1.1 Situation of interest, base case and policy case comparison

The indicator is defined as the capacity to travel to work by active modes tomorrow immediately following a fuel shock which occurs today. Figure 4.1 shows a generic overview on the use of indicators in policy assessment to which has been added information about the indicator. Figure 4.1 also shows that it is possible to compare the base case and policy case indicator values.

The base case is the best estimate of the indicator value if there were a fuel shock today. No policy has been implemented; just as in the current real world. The policy case is an alternative to the current situation. The policy case occurs at the same time as the base case. The policy case could also be called the current situation of the counter-factual scenario. This concept has been applied in transport and geography (see for example Pooley, 2010; van der Horst, 2014). It is the hypothetical indicator value which would exist now, had policies been implemented leading up to the present time. It is possible to compare the base case and policy case indicator values to answer ‘what-if’ policy questions. In addition, both the base case and policy case are based on the present, use surveyed data and minimise the need for speculation about the future. These features seen in Figure 4.1 show that the good indicator criteria (Marsden et al., 2006 discussed in Section 3.3.3) of comparability, measurability and non-corruptibility are accounted for in the indicator scope.

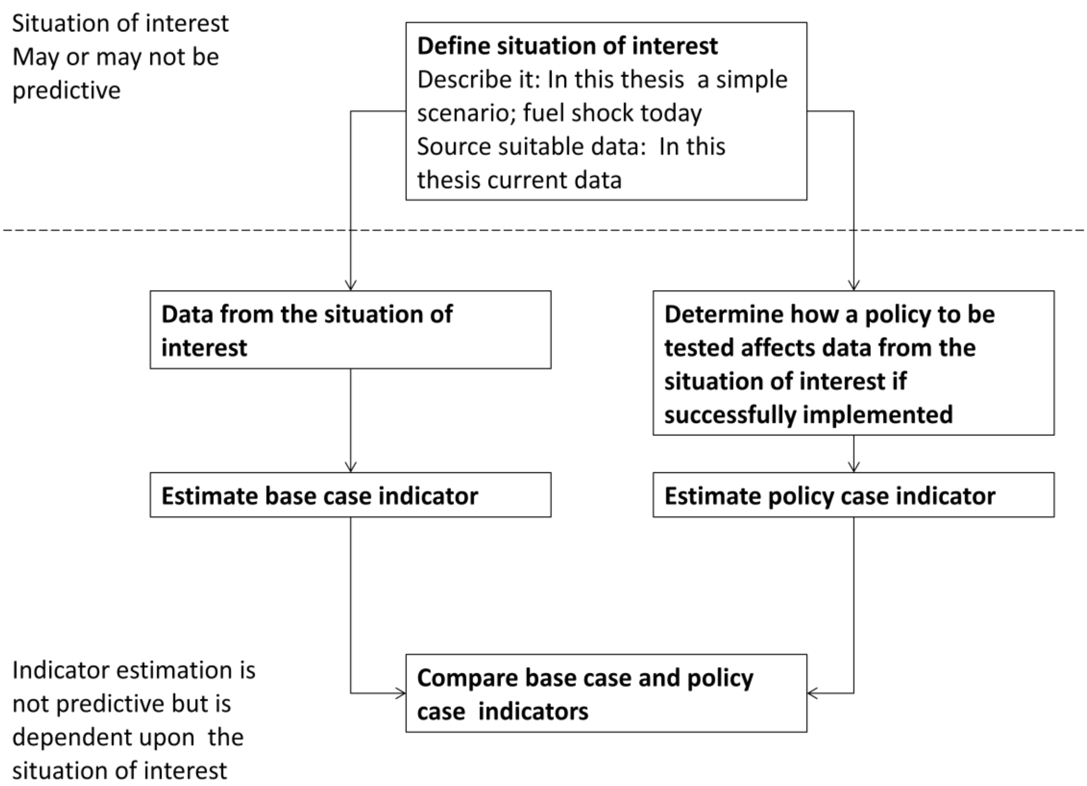

Figure 4.1: A generic overview on the use of indicators in policy assessment with information added defining the base case and the policy case and showing their relation to the separate process of defining the situation of interest.

4.2.1.2 Spatial extent and resolution of the indicator

The indicator will be calculated at a fine resolution at a national extent. This allows a wide range of comparison. Comparisons need to be made between settlements but also within settlements. It is important for this reason that results can be reported for small areas such as US Census blocks[8] and UK Output Areas[9] the latter having an average population of around 300. When testing the effects of policy small area reporting is important; individual or local level processes are better described than when using large scale aggregation which assumes a somewhat homogenous population (Iacono et al., 2010). A 'one size fits all' approach to policy leads to dilution of investment, untargeted interventions and poor outcomes (Ballas et al., 2013; Openshaw, 1995). Small unit reporting also goes some way to alleviating the modifiable unit area problem (Openshaw, 1984). An indicator reported for small areas can be aggregated to district level; seeing results at different

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[8] US census block http://www.census.gov/geo/reference/gtc/gtc_block.html population range 0 ~ 1000

[9] UK Output Area http://www.ons.gov.uk/ons/guide-method/geography/beginner-s-guide/census/output-area--oas-/index.html

levels of aggregation makes analysis mindful of the heterogeneity of areas and helps to avoid the ecological fallacy. Another practical reason for using the smallest available zone is that journey origins have to be calculated based on zone centroid, small zones introduce the smallest error population (Iacono et al., 2010).

4.2.1.3 Direct measurement or index

Indicators can be a direct measurement of one aspect of the system from which a picture of the state of the system can be envisaged. The impact of people on the climate system is envisaged by measuring the CO_2 concentration. Rockstrom et al., (2009) use CO_2 concentration as an indicator. A different form of indicator is an index, an example being the UK Index of Multiple Deprivation (IMD). The IMD does not have units, it ranks areas to allow comparison, but it is not a direct measure of an observable phenomena. The indicator in this thesis will make a direct measurement. An advantage of indicators made using direct measures is that they are more easily understood, there is no need for debate about relative weights of different elements and direct measurement indicators can at a later date be combined with other indicators to make a composite index if required.

4.2.1.4 Sector: people versus freight and types of journey considered

The literature review and discussion of approach has been concerned with individuals and movement of people. Freight movement would undoubtedly be affected by a fuel shock. This would be an important issue to investigate. Attempting to investigate the consequences of fuel shocks on freight and people simultaneously is too broad for a single study. A better approach is to investigate each separately then at a later date integrate the two. This research and indicator will focus on resilience of people to fuel shocks. Commuting journeys, being regular and carried out by the majority of the population are simpler to study than more variable leisure journeys (Pooley and Turnbull, 2000). For simplicity the current focus is commuting journeys.

4.2.1.5 Summary of assumed scenario

The following simplifying assumptions are made regarding fuel availability:

1. Fuel availability stops suddenly today.
2. The government controls and rations any fuel which is available for energy and food supply rather than personal transport and already has contingency plans for implementing rationing in such a situation.
3. Freight is not considered.
4. It is assumed people need to get to work.
5. Walking and cycling are the only effective means of personal transport

4.3 An indicator of the proportion of the population able to get to work after a fuel shock – design overview

Indicators are a trade off between realism and simplicity. The aim is to make non-controversial simplifications and assumptions which are transparent and easy to understand. Simplifying assumptions made in the indicator design are shown in Table 4.1:

Table 4.1: Simplifying assumptions in the indicator scope

1.This is an indicator of adaptive capacity immediately after a shock. 2. The health and age characteristics are the same as the current population. 3. Post shock – walkers and cyclists can use all of the road network 4. Cyclists are free flowing and not subject to congestion or delays at junctions. 5. The population could achieve the level of adaptive capacity proposed by the indicator safely and without risk to health. 6. Spatial distribution of activities does not change the morning after the shock. 7. People cannot migrate or change jobs the morning after the shock. 8. A policy has to lead to safe and healthy outcomes. It cannot encourage or direct people to behave in an unhealthy or unsafe way. For example; estimates of how far people can walk and cycle should not be based on work rates [whilst walking or cycling] and time budgets which lead to illness and injury.

This indicator is given as the proportion of an area's population which *could* maintain their current commute by changing to active modes. It is an indicator of one form of adaptive capacity following a fuel shock. As seen on the left of Figure 4.2, the calculation of the indicator is based on four groups of individual attributes. Firstly, individuals have a maximum capacity to walk and cycle based upon their physical characteristics. Secondly, features such as topography affect this physical capacity. Thirdly the supply of resources such as bike availability and the permeability of the transport network due to barriers and infrastructure also affect the maximum distance which individuals can walk or cycle. Finally individuals have constraints on the time they can spend commuting.

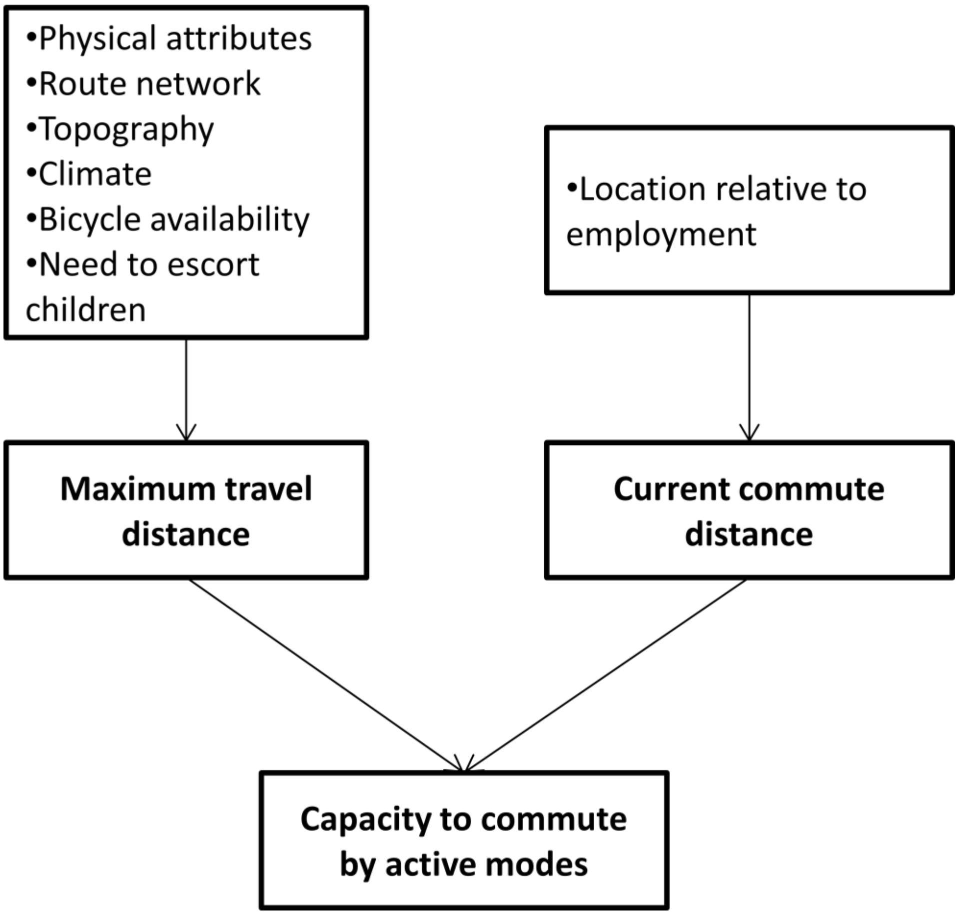


Figure 4.2 Groups of factors determining capacity to commute to work by walking and cycling following a fuel shock.

The conceptualisation of the indicator is shown in detail using an influence diagram in Figure 4.3. The reason for using an influence diagram is to clearly define the relationships between the variables which affect the indicator in an easily understandable way. The notation used here is based on that used in Clemen, (1991). As shown in Figure 4.3, personal physical characteristics such as fitness influence pedalling power. Note that in the cycling stream (the nodes including age, gender and fitness influence a node called “pedalling power”. This in turn influences bicycle speed. In the walking stream, there is no parallel “walking power” node. This is because as will be explained in Section 5.7.2 a simpler model of walking speed is used than that used for bicycling speed. Environmental factors such as slope, supply factors such as bike availability and constraints such as time budget (the length of time which can be spent commuting) affect the maximum distance people can travel by active modes. Maximum travel distance is compared to an individual’s current commute distance to determine whether they can make the journey to work.

The influence diagram shows an expandable design – Other factors could be considered in this design like other fuel availability scenarios. In Figure 4.3 these are shown as greyed out boxes and lines. Though these are beyond the scope of the thesis, it is useful to create the most generic possible indicator design so that it can be broadened and adapted for use with related indicators.

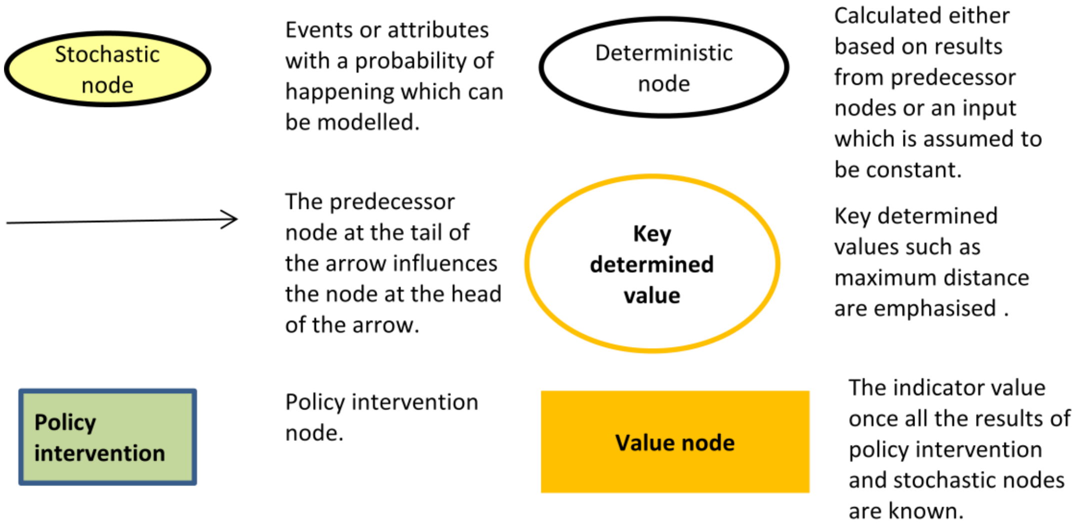
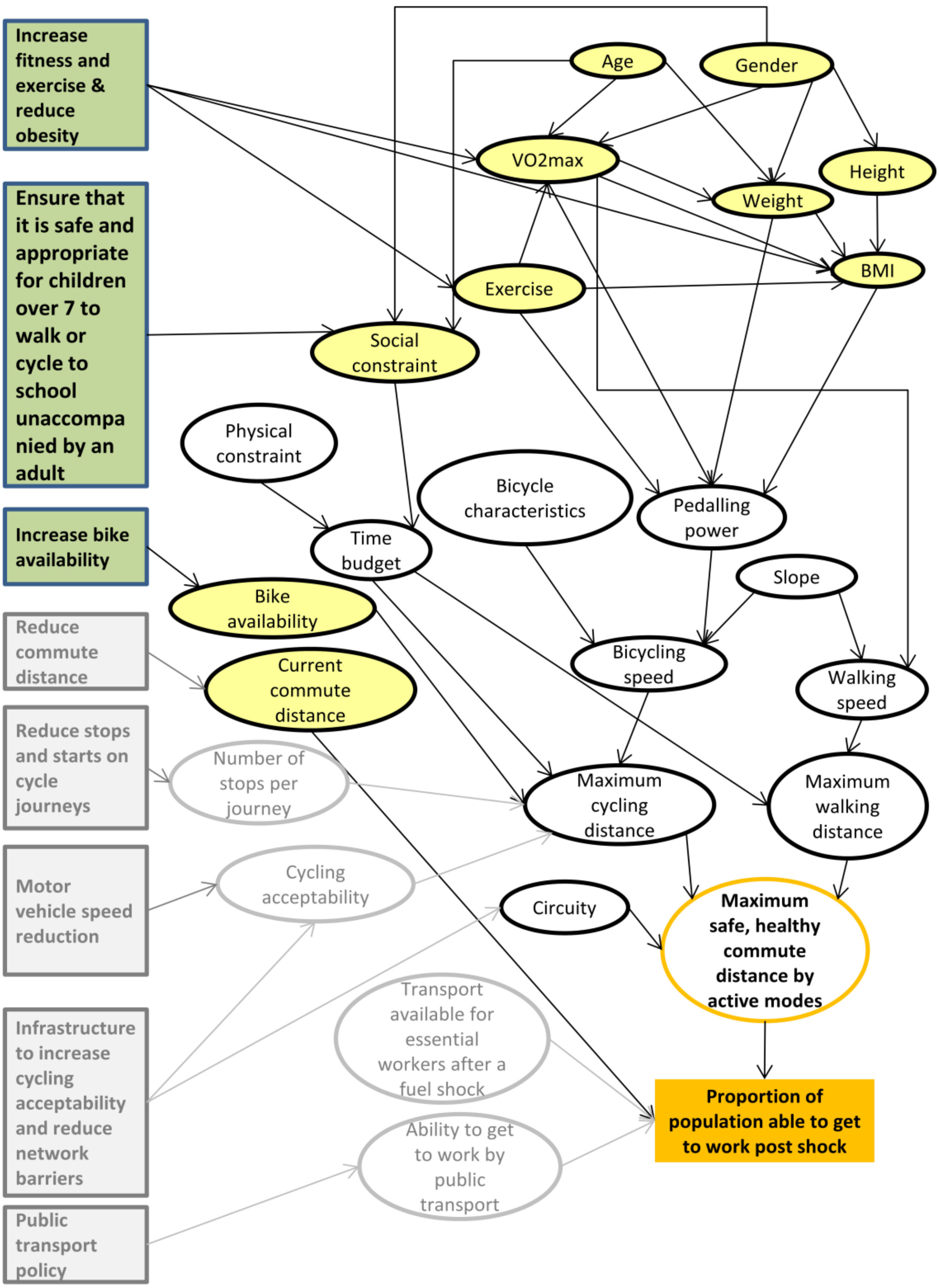


Figure 4.3 The determinants of adaptive capacity to fuel shocks

[overleaf] Influence diagram – factors and relationships modelled in the indicator.
[above] Key for the influence diagram.



4.3.1 Individual attributes and factors which determine adaptive capacity to fuel shocks

Table 4.2 contains a description of the key factors which influence the indicator. The discussion of how these factors are quantified and modelled are discussed in Chapters 5 and 6.

Table 4.2: Key factors influencing capacity to travel by walking and cycling

The discussion of how these factors are quantified and modelled are discussed in Chapters 5 and 6.

Factor	**Description**
Time budget	Time budget is the length of time available for commuting. Two factors constrain the time budget: a *physical constraint* and *a social constraint*. The *social constraint* comes from the pattern of daily life. Governments may issue guidelines on travel times that those seeking work should be willing to travel, for example in the UK it is set as 90 minutes in each direction (DWP, 2012). Not everyone can be expected to do this; some people have mobility impairments and others have demands on time which reduce their commuting time budget – particularly those who have to escort children on the way to or from work. The *physical constraint* on the length of time which can be spent commuting is the body's system of muscles and joints. Any individual who is not already a regular cyclist may be affected by saddle soreness, muscular and joint pain. There is some evidence to suggest that after riding for two hours many experienced riders would express discomfort when using a normal bicycle saddle (Keytel and Noakes, 2002). Discomfort is likely to be felt sooner by those beginning cycling (Christiaans and Bremner, 1998). Mobility impairment and disability is also considered part of the physical constraint. The physical constraint assumes that individuals would be physiologically capable of travelling to work and back five days per week without injury
Pedal Power	Pedal Power is the rate of useful work applied to moving the cranks to propel the bicycle. The UK accessibility statistics travel time calculation methodology assumes that cyclists will travel at 9.9 miles per hour (16km/hr) (DfT, 2012). Forester, (1994)stated that: *"To a cyclist a 5 mile trip is nothing. Under many urban commuting conditions a cyclist could ride 5 miles door to door in less time than a motorist".* Anecdotal evidence in the form of discussions with transport planners is that drawing a 5 mile circle around a development determines its accessibility by bicycle. *"At a very modest pace of 20 km/h, it would take a person 15 minutes to travel 5 km by bike, 30 minutes to travel 10 km and an hour*

	to travel 20 km." (Cycling Embassy of Great Britain, n.d.) (Parkin, 2008) argued that physical effort does not receive sufficient attention when modelling bicycle journeys. None of the statements above take account of variation in physical effort. It is not appropriate to assume that individuals are homogenous. For example assuming that a 19 year old male who exercises regularly and a sedentary 70 year old female can commute the same distance on a bicycle is not appropriate. Assuming a uniform speed for bicycles or taking an average speed is not appropriate as an estimate of maximum distance. Because of this, all of the individual attributes and factors which determine maximum travel distance shown in Figure 4.3, must be taken into account separately. The factors determining Pedal Power are derived from sports science texts and literature (e.g. Jones and Poole, 2004; Pringle and Jones, 2002; Whipp and Rossiter, 2005)
Bicycle characteristics	Bicycle characteristics of interest are those which influence the forces acting on the motion of the bike. Pedal Power, weight, wind resistance and bicycle characteristics are factors determining the speed of a bicycle (Wilson, 2004)
Bicycle availability	Bicycle availability affects the maximum distance people can travel. Except on very steep ground, a person with a bike can travel faster for the same effort than a person on foot. Not everyone has access to a bicycle and this should be accounted for. Anable, (2010) examines socio-demographic data to estimate bicycle availability by income. Bicycle availability increases with income.
Topography	The topography of an area is an important determinant of the maximum distance people could cycle. Cycling uphill is significantly slower than on the flat for a given power input. A route which has an equal amount of uphill and downhill will also have a different power requirement to a flat route for a given average speed.
Climate	factors such as rainfall and temperature affect models of cycle mode choice *behaviour* based on current attitudes (e.g. Wadud, 2014). Only extremes of rainfall and temperature affect *capacity* to cycle. Wind speed however has a direct effect on bicycle speed and therefore maximum travel distance (Wilson, 2004).

4.3.2 Specific policies to test

The influence diagram shows that a wide range of policy options could be tested. During the development of the indicator three specific hypothetical policies will be tested.

Health: This policy has three aspects. Firstly, improve the BMI of the population so no individual is obese (BMI >30). Secondly, ensure all individuals complete the recommended level of exercise; 75 minutes of vigorous exercise per week (DoH, 2011). Thirdly, that individuals have a level of fitness with VO_{2max}[10] rated at least "fair" for their age and gender. The reason for this policy is based on literature which examines health benefits of walking and cycling (de Hartog et al., 2010; Ogilvie et al., 2007; Woodcock et al., 2009)

Bicycle availability: Ensure all working individuals have access to a bicycle. This policy is based on the findings of research into bicycle sharing schemes, research showing the Cuban government attempted to increase bicycle availability (Enoch et al., 2004; Warren and Enoch, 2006) and the physical evidence that an individual with a bicycle can travel further than they could walk.

"Free-range kids": Ensure that it is safe and appropriate for children aged over 7 to walk or cycle to school unaccompanied by an adult.

This adapts thinking behind campaigns by NGOs such as Sustrans promoting the ideas that children should be able to travel safely by active modes, and links to the academic literature which promotes walkability and cyclability as being of value to society (e.g. Bejleri et al., 2011; Steiner et al., 2008).

Policy package: The three policies tested above were tested as a combined package. This is because studies (e.g. Pucher et al., 2010) show that a policy package has a synergistic effect; it has a greater effect than the summed effect of each individual policy.

The policies were chosen because they appear to have the ability to increase the indicator value above the base case. The policies were also chosen because there is existing evidence that promoting walking and cycling in these ways has other benefits over and above the resilience value.

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[10] VO_{2max} (measured in ml per minute per kg of body weight) is a measure of a person's maximum oxygen uptake. It is used as an indicator of cardio-vascular endurance and can also be used to calculate a person's energy use and power output during exercise (McArdle 2010).

5 Methods Considered

5.1 Introduction

Chapters 5 and 6 are concerned with objective 2; developing a method of implementing, for large populations, a model of capacity to make journeys using only walking and cycling which can be used to generate results for the indicator designed in Chapter 4 (which is summarised in Figure 4.3).

The model requires as inputs attributes about individuals to calculate their maximum travel distance and their commute distance. Methods of acquiring these attributes are discussed in Sections 5.2 to 5.4. Section 5.2 justifies the need for attributes about individuals by demonstrating the flaws of using an aggregate model. Section 5.3 explains why relying purely on a survey is not capable of meeting the requirements of the indicator scope (described in Section 4.2). Section 5.4 describes spatial microsimulation, which appears to be a promising methodology to meet the scope of the indicator. The general principles of spatial microsimulation are discussed and examples of previous applications given. Section 5.5 is an evaluation of which spatial microsimulation technique is most appropriate for this investigation. Section 5.6 introduces the most promising spatial microsimulation methodology for use in the case study application of the indicator.

Section 5.7 discusses how individual attributes (identified in yellow in Figure 4.3 as "stochastic nodes") can be used to derive the variables such as pedalling power (identified in Figure 4.3 as "deterministic nodes"). Section 4.3 established that there are relationships between attributes: Fitness (measured as VO_{2max}) and BMI influence a person's pedalling power. The next step, discussed in Section 5.7, is how this relationship can be quantified. The quantification of other deterministic nodes is also discussed; walking speed, time budget, bicycle characteristics and topography.

5.2 The need for individual attributes: Problems with aggregate data input

As explained in the indicator design (Section 4.3), factors such as pedalling power vary between individuals. This is because the individual attributes determining pedalling power vary considerably across the population. VO_{2max} , BMI and amount of time spent doing vigorous physical exercise all influence pedalling power (McArdle, 2010). The variation in these three attributes is shown in Figure 5.1 using data from the 2008 Health Survey for England.

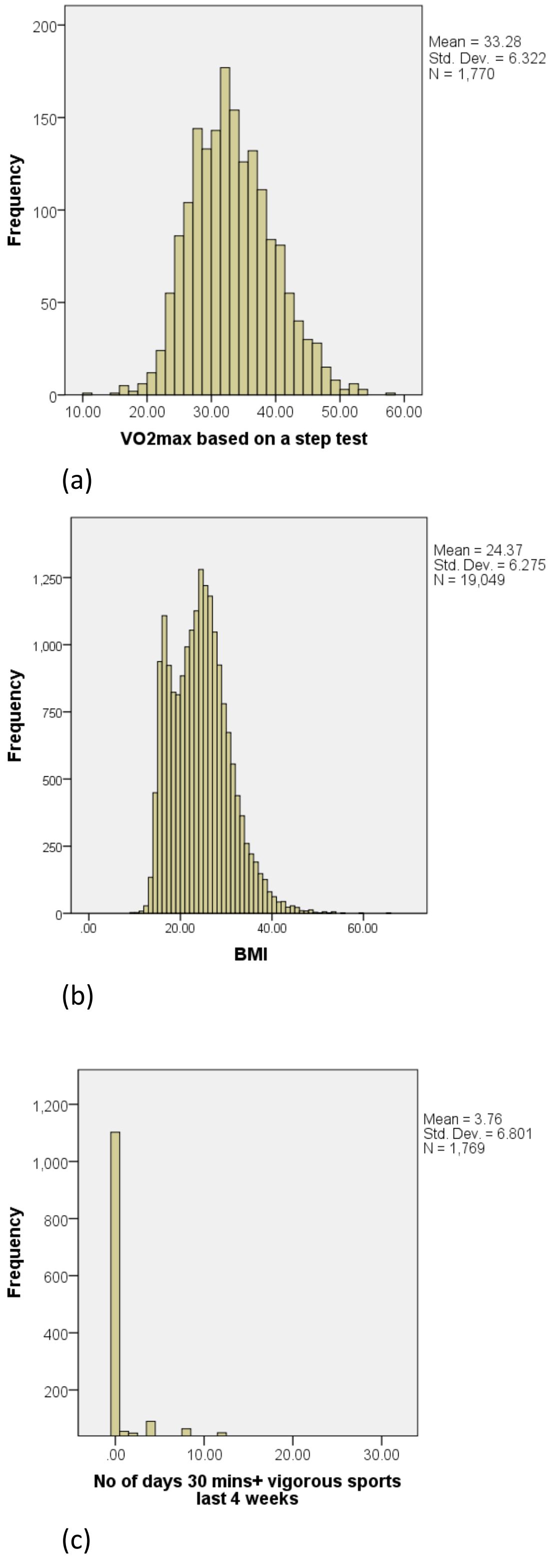

Figure 5.1 The variation in (a) VO_{2max} ml/kg/min, (b) BMI and (c) vigorous exercise amongst participants in the Health Survey For England 2008.

Note not all attributes were measured for all respondents.

Using a model which will be discussed in Section 5.7, the wide range in Pedal Power, (resulting from the attributes in Figure 5.1) can be seen in Figure 5.2.

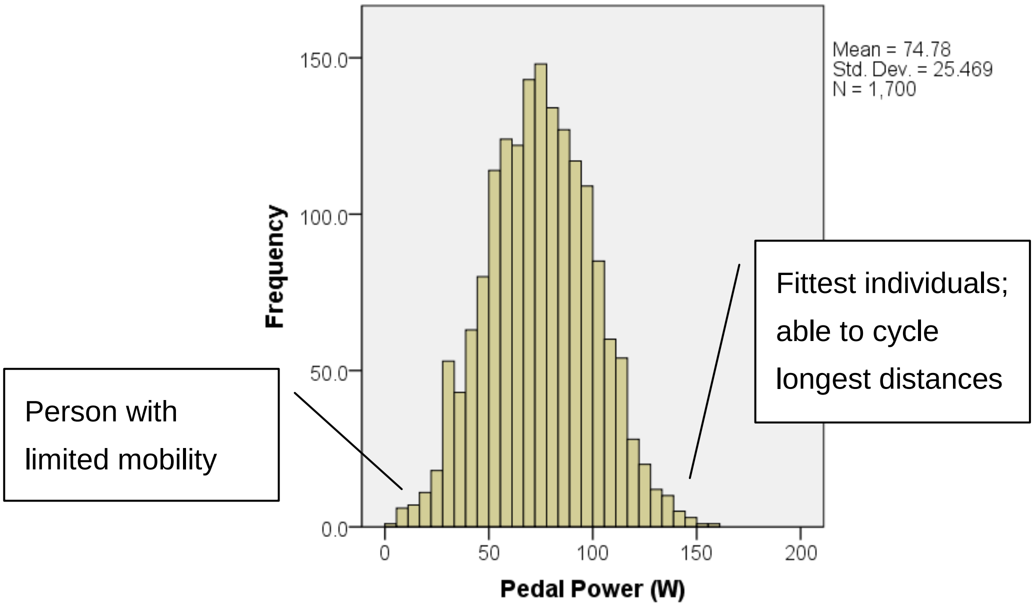

Figure 5.2 Modelled distribution of Pedal Power using data from the Health Survey for England 2008 respondents who completed a step test.

The model used to calculate Pedal Power is discussed in Section 5.7.

If the national mean VO_{2max} and the mean of other attributes were used as inputs to calculate Pedal Power, it would allow a quick calculation of Pedal Power as it would only need to be done once. The problem this causes though is shown by Figures 5.1 and 5.2: Taking the national mean of the attributes above would be an inadequate measure, because it would not take account of the people at the extremes of the distribution. In this indicator people at the extremes of the distribution are of particular interest: For example concentrations of people with very low Pedal Power are indicative of communities which lack adaptive capacity to fuel shocks.

Aggregate models are only calculated once for each zone. This form of calculation would give a crude ‘all or nothing’ indicator value for each zone. The simple example in Table 5.1 illustrates this. Variation within the population of the zone is not accounted for, therefore it does not properly take account of all of the factors identified in Figure 4.3. The scope (in Section 4.2.1) states the indicator is trying to take account of differences between small zones and examine the effects of policies. The differences between zones may be smaller than a crude all or nothing measure. In this context it would not give a satisfactory answer.

Table 5.1 All or nothing indicator values when zonal averages are used

Zone	Average Maximum travel distance	Average commute distance	Indicator value (% of people who could commute by walking and cycling following a fuel shock
A	10km	9km	100%
B	9km	10km	0%

5.3 Individual survey

An alternative to an aggregate model would be to examine attributes of individuals in each zone and calculate for every individual whether they have the capacity to commute to their current work place. However this data is simply not available. Geo-referenced data on the health and fitness of individuals is not placed in the public domain for reasons of confidentiality (Hermes and Poulsen, 2012). It may be possible to carry out a survey, where a sample of the population of each zone are asked questions, which give data for all of the attributes which determine the indicator. However this would be impractical for more than a few zones. The Health Survey for England, is a large national survey which collects data on many of the attributes required to calculate the indicator. It surveys around 25000 people annually with a budget of around £5million (Thomas et al., 2014). Aside from the practical issues of cost, there are two issues here. Firstly, the survey does not have respondents from every small zone (Craig et al., 2009). In England there are over 160000 Output Areas; the smallest data release zones for the UK census. This means that the indicator resolution would be limited to a coarser resolution such as districts. The scope of the indicator (Section 4.2) states that the indicator should be calculable for small areas. Secondly, the Health Survey for England does not release its data with fine geographic detail so it could not be used to calculate the indicator on its own.

The problem then is that the indicator requires information about the attributes of individuals in each particular small zone. This data, which we could call spatial micro-data, is not available.

5.4 Spatial-microsimulation

Spatial microsimulation is a method which has been designed to overcome the problems identified in the previous section: It provides a simulated estimate of spatial micro-data for applications which need it but where the real data is not available. An overview of what spatial microsimulation does is given in Figure 5.3.

Spatial microsimulation takes detailed data about the distribution of individual attributes, which are not released at fine spatial resolution and combines it with a limited range of attributes available as aggregate counts for small areas. The former comes from either a survey of individuals which is nationally representative or from data which provides the conditional probabilities of having a particular combination of attributes. Aggregate data tables for each zone (referred to as constraint tables) are generally taken from a national census. In both the UK (Ballas et al., 2005b; Tanton and Edwards, 2013b), and in studies of other countries, the national census is also commonly used (Beckman et al., 1996; Farooq et al., 2013; Müller and Axhausen, 2010). The output is a synthetic population of individuals containing a wide range of attributes. Synthetic populations are generated for a number of zones that make up a larger study area (e.g. districts in a country, or neighbourhoods in a city). The purpose of spatial microsimulation is succinctly expressed by Ballas et al:

> *"Microsimulation can be defined as a methodology to create large-scale household or individual data sets which can then be used in a what-if fashion to examine the impacts of changes in population structure or government policies." (Ballas et al., 2013)*

The indicator being designed is asking 'what-if?' questions (what if there was a fuel shock?) and examining impacts of a changed situation and different policies.

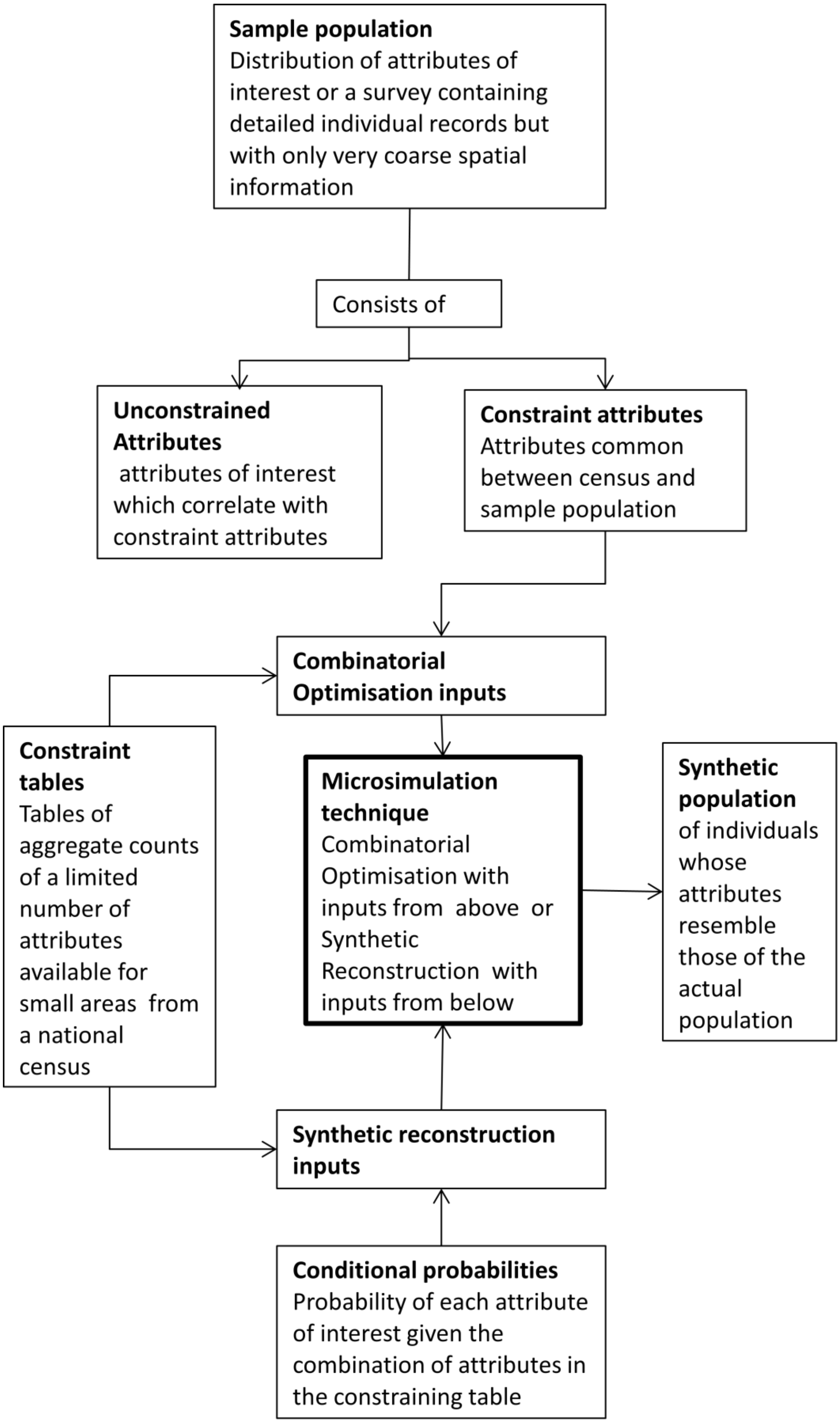

Figure 5.3 An overview of spatial microsimulation.

There are two main groups of spatial microsimulation techniques Combinatorial Optimisation and Synthetic Reconstruction.

5.4.1 History, origins, application and advantages of spatial microsimulation.

Microsimulation originated as an economic tool. Its development is accredited to Orcutt, (1957) and Orcutt et al., (1961) (Ballas et al., 2005b; Clarke, 1996; Hermes and Poulsen, 2012; Tanton and Edwards, 2013b). When applied in economics, microsimulation is used to construct a population of individuals, households or businesses upon which to test the effects of policies such as changes to taxation at the micro-level (Ballas et al., 1999). However, much of this early modelling was at a national resolution (Tanton and Edwards, 2012). The use of microsimulation to analyse the structure of populations and effects of policies in multiple small zones became known as spatial microsimulation which has been used in geography since the 1980s (see for example Clarke and Holm, 1987). Further information detailing the origins of spatial microsimulation can be found in for example Clarke, (1996), and further reviews of the origins, applications and advantages of spatial microsimulation can be found in other recent theses such as Lovelace, (2014) and Campbell, (2011).

The first spatial microsimulation technique to be developed was called Synthetic Reconstruction. Since then a range of techniques have been developed to generate synthetic populations using deterministic and probabilistic Combinatorial Optimisation (Tanton and Edwards, 2012). These techniques are discussed in Section 5.4.2. There is a further classification of spatial microsimulation techniques. The first is static spatial microsimulation; these generate a population at a single point in time. Dynamic spatial microsimulation not only generates a population but applies algorithms allowing it to change over time (Clarke, 1996; Tanton and Edwards, 2012). Only static techniques are considered in this research. This is because the situation of interest in this research (see Section 4.2) is a fuel shock which occurs today. A dynamic spatial microsimulation is not relevant in this case as the indicator is based on current data, the current time and is not based on a predictive model of the future. Should future work be done based on a predictive model of the future, dynamic spatial microsimulation may be useful, though a static model based on the current time is a useful pre-cursor to a dynamic model. For example (Ballas et al., 2006) appear to have used a staged approach to develop first a static then a dynamic spatial microsimulation model.

5.4.1.1 Spatial microsimulation applications

The tasks to which static spatial microsimulation can be applied are to estimate the characteristics of the population in an area for demographic or social analysis and for small area policy modelling such as 'What-if' policy analysis (Ballas et al., 2013; Tanton and Edwards, 2012). Spatial microsimulation has been applied in a range of policy areas: In Health inequality (Campbell, 2011; Edwards and Clarke, 2012; Smith et al., 2007). In transport it is widely used to generate a population of individuals which can then be used in activity based models of transport demand for example Beckman et al., (1996); Guo and Bhat, (2007) and a review by Müller and Axhausen, (2010). In these applications spatial microsimulation is called *population synthesis.* There are other transport applications of spatial microsimulation which attempt to address social policy and inequality themes such as Bonsall and Kelly, (2003) who examined road user charging and social exclusion. Another example is Lovelace et al., (2014) who examined commuter patterns and Lovelace and Philips, (2014) who interpreted this data in the context of commuter fuel poverty arising from increased fuel prices.

Spatial microsimulation is particularly suited to assessing variation in the populations of particular areas and assessing the extent to which they are likely to be affected by policies. This makes it an effective spatial policy modelling tool. Key aspects of the research by Campbell, (2011) involved discerning the spatial pattern of inequalities (in his case health), then examining how policies affect different groups of individuals in different places. The main methodological benefits of spatial microsimulation which facilitate policy analysis are summarised by Hermes and Poulsen, (2012):

> Individual data are produced which capture heterogeneity between areas.
>
> Multiple variables from surveys of individuals can be simulated concurrently saving time
>
> Microsimulation of small areas reduces the effect of modifiable areal unit problems[11].
>
> The problem of lack of detailed data about individuals in small geographies is overcome.

[11]Administrative boundaries are arbitrary. They do not capture natural groupings of people. Modifying the resolution (size of area) or boundary is a change in the areal unit can change results. For example changing parliamentary constituency boundaries affects the result of elections. For further explanation see Horner and Murray 2002 & Openshaw 1984.

The purpose of spatial microsimulation is in line with the aim[12] of the research. There are numerous successful applications of spatial microsimulation in fields related to the current research. The method as outlined above is consistent with the scope of the indicator and requirements of the model. These factors offer justification for adopting spatial microsimulation in this research.

5.4.2 Spatial microsimulation techniques

There are three principal spatial microsimulation techniques which fall into two broad categories. The broad categories are Synthetic Reconstruction and Combinatorial Optimisation (Harland et al., 2012; Hermes and Poulsen, 2012; Tanton and Edwards, 2012). There are two main techniques which apply Combinatorial Optimisation. These are Simulated Annealing and Deterministic Reweighting. The three main techniques are explained below (See also Hermes and Poulson 2012 for a general introduction).

5.4.2.1 The basis of Synthetic Reconstruction

The basis of Synthetic Reconstruction is explained with an example[13]: In this example the synthetic population will contain BMI as an attribute. BMI is a determinant of maximum walking and cycling distance. It is not an attribute collected as part of a national census. BMI is correlated with a number of other personal attributes such as age and gender (McArdle, 2010). Age and gender are found in census tables. A table is taken from the census containing age by gender for each small zone. From another source, the probability of a individual's BMI category given age and gender is obtained. The data source could come either from a survey such as the Health Survey for England or sports science literature such as McArdle, (2010). Each individual is taken in turn and, given their age and gender, a BMI category is assigned. The steps in this process are shown in Table 5.2.

Other attributes could be assigned by increasing the chain of conditional probabilities. A full matrix of conditional probabilities is not always available. Using Iterative Proportional Fitting (IPF), a full matrix of conditional probabilities could be estimated. There may be a cross tabulation of BMI

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[12] The aim of this thesis is to estimate the potential for walking and cycling to enhance resilience to fuel shocks and introduce it as a factor into multi-objective strategic transport planning.

[13] In preparing this example the following references were instructive (Ballas et al., 1999; Clarke, 1996)

category versus age and gender from one source as described above, and from another source proportion of people in each BMI category given education (see Ballas et al., 1999 for further examples). Using IPF, the marginal totals from each table can be used as the basis for a cross tabulation of the probability of being in each BMI category given age, gender and education. These steps are effectively the basis of an algorithm to execute Synthetic Reconstruction in a computer.

Table 5.2 Steps in Synthetic Reconstruction (adapted from Clarke, 1996)

Age by gender is available from the census. This is disaggregated to create a list of individuals across the top of the table. Each row is a step in the process. The probability of being normal weight, overweight or obese for each population sub-group is found in step 2. A random number is drawn in step 3 and the person is assigned a BMI category in step 4.

Steps	**Person 1**		**Person 2**		**Last person**	
1. Age and sex from census table	Age = 18 Sex Male		Age = 60 Sex male		Age 50 Sex female	
2. Probability of obesity given age and gender	P normal weight = 0.8 P overweight = 0.1 P obese = 0.1	Cum prob bin N = 0.8 Ow 0.81-0.9 Ob = 0.9-1	P normal weight = 0.5 P overweight = 0.3 P obese = 0.2	Cum prob bin N = 0.8 Ow 0.81-0.9 Ob = 0.9-1	P normal weight = 0.4 P overweight = 0.4 P obese = 0.2	Cum prob bin N = 0.8 Ow 0.81-0.9 Ob = 0.9-1
3. Draw a random number	0.7		0.6		0.1	
4. Assign BMI category	normal		overweight		normal	

As well as categorical values, scale attributes can be allocated to individuals. Fitness could be added to the example above. If the distribution of VO_{2max} were available for each sub-group of the population e.g. men aged 16-34 with normal BMI, then VO_{2max} can be allocated probabilistically. However to have a representative distribution of values such as this may require a large survey or sample population. If a large survey is available which contains all the useful individual attributes, a Combinatorial Optimisation technique may be more useful.

5.4.2.2 The basis of Combinatorial Optimisation

The data requirements for Combinatorial Optimisation techniques are:

Sample population: A table containing data about individuals taken from a survey such as the Health Survey for England. In spatial microsimulation literature this table may also be called microdata, or a microdata sample.

Constraint table: A table of data from the census. It contains counts of the number of people with a particular attribute resident in a particular area. Constraint attributes are common to both the census and the sample population. The attribute is broken down into different categories; gender for example is broken down into male and female. In spatial microsimulation literature this table may also be called a small area data tabulation. A simplified example of a sample population based on micro-data is shown in Table 5.3.

Table 5.3 A simplified version of a sample population table

Columns common to the sample population and the census are orange and used as constraints. Unconstrained attributes are shown green – these are found only in the sample population and not the census.

Person number	**Age**	**Gender**	**Fitness (VO_{2max})**
1	18	Male	48
2	60	Male	25
3	25	Female	42
4	52	Female	26

From the sample population, potential constraint tables and attributes are identified. These are attributes common to both the sample population and the available small area constraint tables (Shown in orange in Table 5.3 and blue in Table 5.4). For example if there is a small area census table available which shows the number of people in each area by age and gender, then the possible constraints are age and gender. There are no constraint tables which contain fitness. If we wish to simulate the fitness of the population, we have to choose constraint attributes which are strongly correlated with fitness. Age and gender are correlates of fitness (McArdle, 2010) so they are suitable constraints. Combinatorial Optimisation then uses one of several algorithms to pick a combination of individuals from the sample population that matches the aggregate count of attributes for each zone in Table 5.4.

Table 5.4 An example constraint table; population by age and gender

Attributes common to the census and the sample population are shown in blue.

Zone	Male<= 50	Male >50	Female < =50	Female >50
1	2	1	1	1
2	6	4	2	7

In this simple example for zone 1:

Person 1 would be chosen 2 times because Table 5.4 shows there are 2 males under 50.
Person 2 would be chosen 1 times time because there is one male over 50.
Person 3 would be chosen 1 times time because there is one female under 50.
Person 4 would be chosen 1 times time because there is one female over 50.

The result is a synthetic population for zone 1 where each individual has the attributes age, gender and fitness. In a real application, all the attributes of interest are available in the sample population along with a range of potential constraint attributes. Constraints can be chosen based on those which have the strongest correlations to the unconstrained attributes (see for example Williamson, 2012).

5.4.2.3 Algorithms used in Combinatorial Optimisation

Deterministic or stochastic algorithms can be used in Combinatorial Optimisation; they are often referred to as *Deterministic Reweighting* or *Simulated Annealing*. Simulated Annealing is the most used stochastic algorithm but other procedures such as genetic algorithms are also used (Williamson, 2012). Examples of static spatial microsimulation applications using Deterministic Reweighting include (Ballas et al., 2005a; Edwards and Clarke, 2012; Lovelace et al., 2014). Simulated Annealing based applications include those by Farrell et al., (2012) Harland et al., (2012) and Voas and Williamson, (2001).

5.4.2.4 Deterministic Reweighting

A simple example of Deterministic Reweighting is given below following instructions given in Chapter 9 of Ballas et al., (2005c).

The data requirements are a sample population and at least one constraint table (these tables are described in Section 5.4.2.2). **Step 1:** Take the sample population (Table 5.5) and give each individual a starting weight. The starting weights account for bias and errors encountered when a survey is carried out.

Table 5.5: A simplified version of a sample population table

It is a redrawn version of Table 5.3 with starting weights added

Person number	**Age**	**Gender**	**Starting Weight** w_i
1	18	Male	1
2	60	Male	1
3	25	Female	1
4	52	Female	1

Step 2: Choose a constraint Table based on a small area data tabulation from the census. Table 5.5 is a hypothetical example.

Table 5.6 A hypothetical constraint table; population by age and gender for a single zone

Age	**Male**	**Female**
Under 50	2	1
Over 50	1	1

s_{ij} when reweighting the first individual in Table 5.5

Step 3: Redraw the sample population table as a cross-tabulation so that it can be compared to Table 5.7. Note that the weights do not match between all cells of Tables 5.6 and Table 5.7.

Table 5.7 Cross tabulation of the sample population

Age	**Male**	**Female**
Under 50	1	1
Over 50	1	1

m_{ij} when reweighting the first individual in Table 5.5

Step 4: The weights should be adjusted. Multiply the original weight w_i (shown in Table 5.5) by the element *ij* of the census constraint s_{ij} (shown in Table 5.6) and divided by the element *ij* of the sample population cross tabulation m_{ij} (shown in Table 5.7). This results in a new weight for each individual in Table 5.5 n_i.

$$n_i = w_i \times \frac{s_{ij}}{m_{ij}}$$

[5.1] after Ballas et al., (2005c p40).

The process carried out by equation 5.1 is similar to the Furness method used in transport modelling (Norman, 1999).

Table 5.8: Sample population table with new weights shown

Person number	**Age**	**gender**	**Starting Weight w_i**	**New weight n_i using equation [5.1]**
1	18	Male	1	1x2/1 = 2
2	60	Male	1	1x1/1 = 1
3	25	female	1	1x1/1=1
4	52	female	1	1x1/1=1

Table 5.9 Reweighted Cross tabulation of the sample population

Age	**Male**	**Female**
Under 50	2	1
Over 50	1	1

After reweighting, this cell matches its corresponding cell in Table 5.6.

Step 5 If there are multiple constraint tables these are reweighted by repeating steps 2-4. A number of iterations may be required before the cross tabulation of the sample population matches the constraint table.

Step 6 The final weights are the estimated probability of each person in the sample population being found in the area described in the constraint table (Ballas et al., 2005c). In this simple example all the final weights are integers. In a large practical application many of the final weights will not be integers. As it is not possible to have 0.3 of a person these weights have to be integerised. There are a variety of algorithms for doing this including Ballas et al., (2005c) and (Lovelace and Ballas, 2013). These algorithms produce a final synthetic population of complete individuals replicated from the sample population, which can now be applied.

5.4.2.5 Simulated Annealing

Simulated Annealing randomly selects individuals from the sample population to form the initial population of a zone. The error is measured. Individuals in the initial population are replaced at random. If there is a reduction in error, the replacement is kept. Unlike hill climbing algorithms, which only allow selection of a better result, Simulated Annealing will sometimes, based on a probability function, allow a worse result (Harland et al., 2012; Williamson, 2012). The reason for this is to avoid solutions which are stuck in regional minima. Simulated Annealing is an algorithm taking its name from the process called Annealing which occurs in metals as they cool (Rahman et al., 2010). The rate of cooling affects the formation of crystals in the metals, which affects the metallurgical properties. Controlling the cooling allows formation of stronger metals. The metaphor is used because controlling the rate of 'cooling' is akin to controlling the rate at which a worse solution may be accepted. During the running of the algorithm, when the temperature is high in the early stages, a worse solution is likely to be allowed, but as the temperature cools towards the end, worse solutions are rarely accepted (ibid.). The algorithm is based on the work of Metropolis et al., (1953).

The pseudo code and flow diagram in Figure 5.4 below illustrate how the Simulated Annealing algorithm works. This description references Williamson, (2012), (Harland, 2013) and Harland et al., (2012). The algorithm begins with several set up steps before loops which run during execution.

Suppose that the sample population in Table 5.3 and the constraint Table 5.4 are available:

Set-up

Set up tables (present the data as in Tables 5.3 and 5.4)
Set a start temperature (e.g. 100)
Set cooling rate (e.g. 1 per iteration)
Count the number of people in zone1 (from Table 5.4)
Randomly sample a population of the correct number of people from the sample population (Table 5.3)

While the temperature is greater than 0 and the Total Absolute Error[14] (TAE) >0 run the following loops:

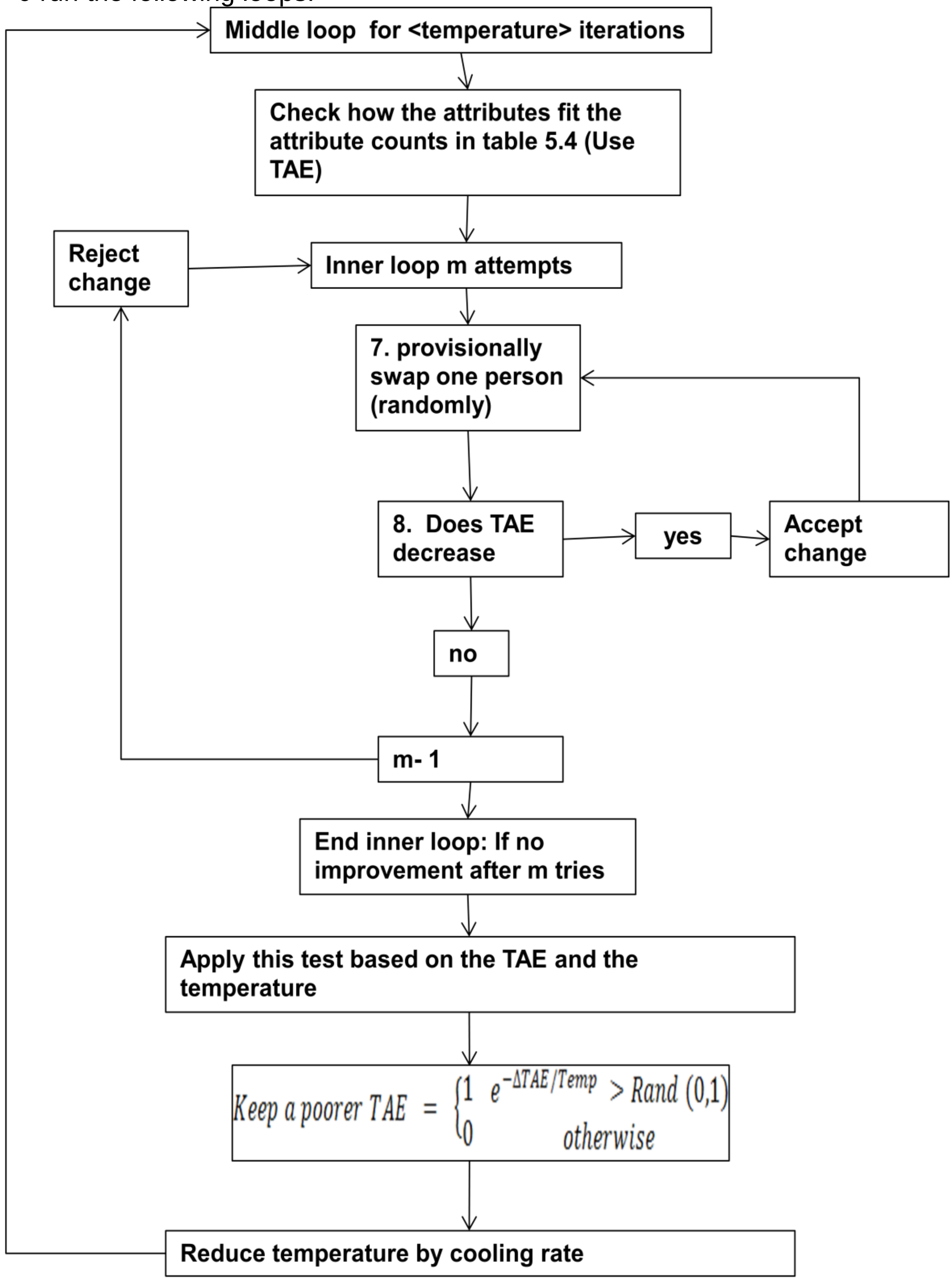

Figure 5.4 Looped procedures in the Simulated Annealing algorithm

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[14] Harland, (2013a) uses TAE as the error measure in the Flexible Modelling Framework software. However other error measures could be used in the algorithm e.g. Williamson, (2012) uses a modified z score as a selection measure.

5.4.2.6 Summary of key features of three spatial microsimulation techniques

A brief summary is given in Table 5.10

Table 5.10 Summary of key features of three spatial microsimulation techniques

Technique	**Sample population required**	**Deterministic**	**Stochastic**	**Range of applications**
Synthetic Reconstruction (SR)	N	N	Y	Y
Deterministic Reweighting (DW)	Y	Y	N	Y
Simulated Annealing (SA)	Y	N	Y	Y

5.4.3 Validation procedures available for spatial microsimulation outputs

Effective modelling techniques require effective validation procedures. This section describes the main validation procedures available for spatial microsimulation. The validation of the synthetic population attempts to assess the extent to which the synthetic population is a realistic representation of the actual population. This is the basis of validation in spatial microsimulation (Edwards et al., 2011; Edwards and Tanton, 2012; Voas and Williamson, 2001); Smith et al., 2009) If the population is realistic, then when their attributes are used to calculate small area estimates (such as the capacity to commute by walking and cycling), it contributes towards confidence in the result. A principle of good indicators is that they should be ‘measureable’ using sound validated methods as discussed in Section 3.3.3.2.

Spatial microsimulation models can be internally and externally validated (Tanton and Edwards 2012; Voas and Williamson, 2001). Internal validation tests constrained attributes; those common to both the constraint tables and the sample population. First the synthetic population is aggregated to the same resolution as the constraint tables. Measures then test the extent to which the constrained attribute matches the constraint table count for that attribute. This is also called validating the internal goodness of fit. External validation evaluates the fit of unconstrained attributes; those found in the sample population but not in the constraint tables. External validation of spatial microsimulation models is very difficult (Edwards and Tanton, 2012). This is because the reason for using spatial microsimulation in the first place is a lack of data covering all the attributes of interest at the spatial resolution and extent required. This means that there is usually little or no data available to validate against (Edwards and Tanton, 2012) – though a range of techniques are available to make use of what little data is available.

5.4.3.1 Internal validation

There is no single accepted procedure for validation of spatial microsimulation models but a variety of techniques (based on absolute errors, standardised errors and statistical measures) have been used (Edwards and Tanton, 2012). These are discussed below.

Error statistics based on Total Absolute Error are useful because of their simplicity argue Harland et al., (2012). In a spatial microsimulation model Total Absolute Error is the number of people in the population that have been misclassified in some way (Voas and Williamson, 2001). In calculating TAE, T_{ij} is the simulated population cell count and E_{ij} is the expected cell count (the constraint table value). Subscripts *i* and *j* denote the cell's position, *i* is the i^{th} attribute category, *j* is the code for the Output Area. Total Absolute Error for all zones is shown in equation 5.2, but TAE is used in checking the fit of individual zones shown in equation 5.3

$$TAE = \sum_i \sum_j \left|T_{ij} - E_{ij}\right|$$

[5.2]

$$TAE_j = \sum_i \left|T_{ij} - E_{ij}\right|$$

[5.3]

As a raw value TAE can be misleading; it shows the number of people misclassified but without the context of the population size (Edwards and Tanton, 2012). Additionally TAE double counts misclassified people (e.g. the person who has been allocated a limiting illness who should not, and the person who does not have a limiting illness who has not been allocated one) (Harland et al., 2012). To avoid this TAE/2 is used and referred to as the classification error. The more useful measures derived from TAE take account of the population because a large TAE in a large population is not such an important error as a large TAE in a small population (Edwards and Tanton, 2012). One measure is Standardised Absolute Error (SAE = TAE / population) another, Percent Cell Error, is used by Harland et al., (2012). Percent cell error *PE* is "the percentage of individuals which have been misclassified in a cell, zone or attribute"(Harland et al., 2012).

$$PE = \frac{\left(\frac{TAE}{2}\right)}{population} \times 100$$

[5.4]

Another approach is bivariate regression analysis. It can be used to assess the fit between simulated and expected values. The R^2 value indicates the association between simulated and predicted attributes, but the best fit line on a regression scatter plot may not be the ideal fit y=x (simulated = predicted) (Edwards and Tanton, 2012).

The criticism of TAE and R squared based measures is that the statistical significance of the errors is not evaluated. Tests based on the Z score were found to be the most useful for evaluating spatial microsimulation outputs (Voas and Williamson, 2001; Williamson, 2012). Voas and Williamson, (2001) reviewed 12 different measures and drew their conclusion as to the most appropriate method based on familiarity, ease of calculation and the ability to show whether differences are statistically significant.

The Z score calculation first involves calculating the expected small area count for cell[15] *i* in constraint table *j;* E_{ij} and the simulated count for cell i in constraint table j; S_{ij}. N_j = the count in table $_j$. Proportions are then calculated. $p_{ij} = \frac{E_i}{N_j}$ is the expected proportion of counts falling in the cell, and $t_{ij} = \frac{S_i}{N_j}$ is the simulated proportion of counts falling in the cell. t_{ij}, p_{ij} and N_j can then be inserted into equation 5.5 to calculate the z score.

$$Z_{ij} = \frac{(t_{ij} - p_{ij})}{\sqrt{\frac{P_{ij}\,(1 - P_{ij})}{N_j}}}$$

[5.5] (Williamson, 2012 p31).

[15] A cell contains the count of people with a particular category of a particular attribute such as people in category 'male' in the attribute 'gender'

The fit of rows for an entire table can be assessed by squaring the z score for each cell in the table, summing the result and comparing this score to a chi square table where the degrees of freedom are equal to the number of cells in the table (Williamson, 2012).

As well as assessing fit based on individual cells and tables, it is useful to have a measure which flags up zones that are poorly simulated. As well as z scores, SAE can be used to identify poorly simulated zones and also to check that most areas are well simulated. A rule of thumb to identify a poorly simulated area is if SAE exceeds the total population (Edwards and Tanton, 2012). Smith et al., (2009) suggest that overall the SAE should be below 20% in 90% of areas.

5.4.3.2 External validation

As mentioned above external validation (validation of unconstrained values) is difficult because of the lack of data to validate against (see for example Edwards and Tanton 2012; Ballas and Clarke, 2001). This is generally the case though an exception to this is (Smith et al., 2011) who validated a spatial microsimulation of smoking behaviours against the New Zealand census which in 2006 included smoking behaviour (a variable not usually found in a national census). One solution is based on aggregating the simulated data to a larger geography (Edwards and Tanton 2012). The idea is illustrated with this example. A synthetic population is created for all the districts in the country. One of the un-constrained attributes is VO_{2max} [16]. A separate survey to the one used to make the sample population gives a national average value for VO_{2max}. By aggregation of the synthetic population, the simulated national average could be compared to the separate survey. This would give a validation measure. This measure is however rather coarse; it gives a broad indication of the fit of an unconstrained attribute, but not whether that attribute has been fitted correctly in small areas (Edwards and Tanton, 2012).

Alternative methods are available. One is to carry out a survey of attributes in a small number of areas, then compare this primary data to the simulation. There may be practical difficulties in terms of ethics, cost, time and response rates (Edwards and Tanton, 2012). Another approach which may work in

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[16] Unconstrained means VO2max appears in the micro data sample but not in the census constraint tables. Referring to an earlier example; VO2max appears in sample population Table 5.3 shaded green for unconstrained, but does not appear in Table 5.4 the constraint table.

some situations is to compare an unconstrained attribute to a similar highly correlated attribute (where r > 0.5). For example Edwards et al., (2011) compared obesity, which was an unconstrained attribute, to known information on the spatial distribution of certain cancers which are strongly associated with obesity (for further examples see for Anderson, 2012; Tanton et al., 2012). A final method of validation is to ask practitioners “does this look about right?” (Edwards and Tanton, 2012). This is only a qualitative and arguably somewhat subjective validation method. Also, though it seems a quick and easy test, it would still require the time to conduct an ethical review to carry out a survey of practitioners.

5.4.3.3 Reasons for poor validation

There are a great many reasons why validation results might be poor and these are summarised in (Edwards and Tanton, 2012).

- Sample population too small; the individuals in the sample population do not contain enough variation to represent the whole population
- Too many or too few constraints
- Different constraint combinations give different results
- Regional differences not identified by a national survey
- Poor choice of sample population and constraint data sets
- Choice of technique
- Spatial resolution of simulation

5.5 Evaluation: Which spatial microsimulation technique is most suitable?

This section discusses the pros and cons of the microsimulation techniques described above for producing an indicator of who could get to work by walking and cycling if there was no fuel available for motor transport at a fine resolution. The performance based assessment criteria are; internal and external goodness of fit. There are a number of other evaluation criteria; speed of computation, work required in data preparation, whether a sample population is required; whether the order of constraints has an impact on results, and whether additional attributes can be added to the population without re-running the microsimulation.

5.5.1 Performance

Performance of microsimulation techniques has been assessed by other researchers. They used measures based upon the validation techniques described in Section 5.4.3. As described in Section 5.4.3, good performance on internal validation tests (also known as high internal goodness of fit) increases the chance that the model gives a realistic representation of the population of the zones of interest. Harland et al (2012) tested the internal goodness of fit of Simulated Annealing, Deterministic Reweighting and Synthetic Reconstruction techniques when given the same input data and constraints using UK data. They tested three fine resolution census geographies: MSOA, LSOAs and OAs[17], with populations of ~6000, ~1500 and ~300 respectively. At both LSOA and OA geographies, Simulated Annealing out performed Synthetic Reconstruction in terms of percent cell error. Percent cell error is "the percentage of individuals which have been misclassified in a cell, zone or attribute"(Harland et al., 2012). Their Simulated Annealing tests had no error at LSOA and OA resolution. At OA level using the same data, the percentage cell error for Synthetic Reconstruction varied from 0.02% to 3.2%. Both considerably out performed Deterministic Reweighting which had between 2.3% and 32% cell error (Harland et al., 2012). This work showed that over and above the quality of data available, the techniques performed differently.

Williamson, (2012) carried out a comparison of Simulated Annealing and Synthetic Reconstruction using 1991 census data. The assessment used a wider range of tests than Harland et al., (2012). TAE based testing showed Simulated Annealing performed better. Evaluation was made using z-scores and related variants. Simulated Annealing again performed better. The overall assessment by Williamson, (2012) was that Simulated Annealing out performed Synthetic Reconstruction in almost every respect.

There are other practical benefits to using Combinatorial Optimisation techniques. Firstly, the synthetic population only needs to be constructed once whereas Synthetic Reconstruction populations should have multiple draws because of the greater variation between each draw. This gives both a computing time and a data storage benefit to Combinatorial Optimisation methods (Williamson, 2012). Williamson made 100 versions of the synthetic population and found that with Simulated Annealing the variability in poorly fitting cells and tables was low. Williamson (2012) states that a Simulated Annealing based synthetic population has a 'guaranteed good fit' (This presumably is subject to the data available) and that in general only a single synthetic population need be created. Additionally Combinatorial

[17] Medium Layer Super Output Areas (MSOA) , Lower Layer Super Output Areas (LSOA), Output Areas (OA). Further details are given in Figure 7.2

Optimisation more easily allows the inclusion of unconstrained attributes (Hermes and Poulsen, 2012). There is a further issue raised by Synthetic Reconstruction and Deterministic Reweighting methods. The order in which constraints are added has an effect on the outcome thus introducing further complications (Clarke, 1996; Huang and Williamson, 2001).

5.5.2 Other evaluation criteria

Despite the superior performance of Simulated Annealing there are reasons to use other techniques in some circumstances. For example, Deterministic Reweighting is computationally less intensive than the other techniques so has shorter run times (Hermes and Poulsen, 2012). Barthelemy and Toint, (2012) and Ballas et al., (2005a) make the following points in favour of Synthetic Reconstruction. Firstly, Synthetic Reconstruction is useful in the absence of a sample population. Second, Combinatorial Optimisation methods require that the constraint tables be available at the same scale; that is all constraints have to be available at Output Area resolution if the model is to be made at that scale. Third, constraint tables have to be consistent. Barthelemy and Toint, (2012) explain that if multiple constraint tables are being used e.g. education in one table and sex by age in another, then the margin totals should be the same; in each zone the different tables should have the same population total. For small zones such as the UK census Output Areas, where the population is only ~300, small counts of certain attributes could identify individuals. In order to preserve anonymity national census organisations deliberately introduce small inconsistencies to some constraint tables (Stillwell and Duke-Williams, 2003). A solution to this issue described by Barthelemy and Toint, (2012) is to take the total population of each zone from a reference table. All cell counts are then calculated as frequencies. To illustrate this idea, imagine a zone with a total of 49 residents in one of the constraint tables that is referred to as the reference table. A second constraint table which looks like Table 5.11 has had inconsistencies deliberately introduced so the population total is not consistent with the reference table. The inconsistent table is corrected by converting the cell counts to frequencies and rounding the counts to integer values (Table 5.12). In this simple example, rounding gives integer values which match the reference population total. In real applications a lossless rounding procedure is required which gives table totals consistent with the reference table.

Table 5.11 An inconsistent table

Where the sum of individuals in all categories is not equal to the total population

Category 1	**Category 2**	**Category 3**
20	20	12
Total 52.		

Table 5.12 The inconsistent table corrected as frequencies and rounded

Category 1	**Category 2**	**Category 3**
20/52 * 49 =18.84	20/52 * 49 =18.84	12/52 * 49 =11.3
19	19	11
Total 49.		

A relatively simple Synthetic Reconstruction model should be the easiest to construct, as there is no sample population table to produce. However, as more attributes are added, an iterative proportional fitting process may be needed to estimate a full matrix of conditional probabilities as explained in Section 5.4.2.1. Synthetic Reconstruction and Deterministic Reweighting are affected by the order in which the constraints are added. Evaluating the most appropriate constraint order is another data processing step. Deterministic Reweighting and Simulated Annealing require the building of constraint tables and a sample population table. If unconstrained attributes are required then data exploration is required to find constraints that they are correlated with. All techniques require more data processing at fine resolution than at coarser resolution because of the need to account for deliberately introduced errors in the constraint tables.

Another advantage of techniques using a sample population is that the synthetic population are cloned depictions of 'real people'. They have a range of attributes as wide as the survey from which the sample population was built. Surveys such as the Health Survey for England collect several hundred pieces of information about their respondents. Ballas et al., (1999) explains that these extra attributes could be used to produce further information about the population of the small zones in the study area. This suggests that building a synthetic population using the Simulated Annealing or Deterministic Reweighting techniques described in Section 5.4.2 creates a general purpose population containing a vast array of attributes. However, the usefulness of these extra attributes are subject to external validation tests. Depending on the tests, it may be appropriate to use some additional attributes without rerunning the spatial microsimulation for another purpose at a later date. A summary of the evaluation of the three spatial microsimulation techniques described in Section 5.4.2 is given in Table 5.13.

Table 5.13 Summary of evaluation of spatial microsimulation techniques according to different criteria

	Deterministic Reweighting	**Synthetic Reconstruction**	**Simulated Annealing**
Internal validation (Internal goodness of fit)			Best performing
External validation			Best performing
Speed of computation	Best performing		
Data preparation		Quickest in a relatively simple model	
Need for sample population containing all attributes	Y	N	Y
Order of constraints has an impact	Y	Y	N
Additional attributes can be added without rerunning the model	With caution	N	With caution

5.6 A novel static spatial microsimulation method

The conclusion drawn from Section 5.5 is that using an existing spatial microsimulation technique is not ideal in the construction of the indicator. To address this, a new technique is developed using a two stage hybrid spatial microsimulation. It is a hybrid of Simulated Annealing Combinatorial Optimisation and Synthetic Reconstruction. This new method will be used in the development of the indicator and forms part of the original contribution of the thesis.

The principal problems of using an existing technique are: Firstly, to use an existing technique would require sacrificing either spatial microsimulation performance or limiting the inputs to the indicator. Simulated Annealing based Combinatorial Optimisation is the best performing when applied to small areas. However this technique requires that all attributes to be simulated are found in the same micro-data sample. It is anticipated that in an application of the indicator it will not be possible to find all attributes in the same micro-data sample. Synthetic Reconstruction can be applied where a micro-data sample is not available. However this would forgo the performance advantages of Simulated Annealing at the smallest geographies as well as the practical benefits of not having to consider the order of constraints or the potential for adding additional attributes to individuals (explained in Section 5.5.2 and summarised in Table 5.13). Errors from Synthetic Reconstruction are smaller with larger zones, but, as explained in Section 4.2.1.2, using large zones is also problematic when calculating walking and cycling measures (Iacono et al., 2010). Secondly, some attributes cannot be assigned to an individual until that individual has been allocated a location. For example, commute distance is strongly associated with location as well as individual socio-demographic attributes. Commute distance is collected in some micro-data surveys, but, it would not be appropriate to allocate this value out of its original spatial context. This is because individual survey data has geographical detail removed. This means that some individuals will not be allocated to areas to where they actually live.

To overcome these problems, the case study application of the indicator will generate a synthetic population using a two stage hybrid spatial microsimulation. A brief description and rationale are given below. The process is described more fully in Chapter 6 and its application with English data is explained in Chapter 7. The two stage hybrid method will work as follows: In the first stage, a single synthetic population is constructed using Simulated Annealing. The available micro-data is used as a sample population and constraint tables are taken from the census. In the second stage, Monte-Carlo sampling (Synthetic Reconstruction) is used to add attributes which are not available in the micro-data or which are geographically dependent. Monte-Carlo sampling can then be used to draw multiple synthetic populations.

This approach makes progress towards addressing the problems above: The performance benefits of Simulated Annealing are used with available data. Though Monte-Carlo sampling introduces increased computing time and data storage requirements, this is less of a drawback than it once was. A greater gain is made because it allows the full range of desired attributes to be modelled rather than having a model constrained by limited data sources. Introducing Monte-Carlo sampling also introduces a source of stochastic variation. This is not a problem if a suitable number of draws is made; the standard error of the mean should not be excessive. Therefore the confidence interval for the base case indicator should also not be too great to usefully make comparison between areas[18]. Because only a minority of attributes are being added using Monte-Carlo sampling, the stochastic variation between draws should be less than if the entire population was built using Synthetic Reconstruction. This will give an overall advantage in terms of performance.

In stochastic models it is useful to save the seed values used by the computer's random number generator. This is so that the same result can be obtained if comparison is to be made between a base case and a policy case. In this methodology, the equivalent of saving the seed value can be achieved by saving all the attributes of the individuals generated in each draw. When a policy case is calculated, the saved individuals are used, they are not rebuilt from scratch, so there is no stochastic difference between individuals used in the base case and policy case calculations (this is explained further in Section 6.6). A two stage approach also solves the problem of assigning attributes associated with location such as commute distance.

5.7 Deriving model inputs from individual attributes

Once individual attributes have been generated by spatial microsimulation, some will need to be combined to quantify variables used as inputs to the model. This section discusses how individual attributes (identified in yellow in Figure 4.3 as "chance nodes") can be used to derive model inputs. The model inputs derived from individual attributes are a subset of the "deterministic nodes" identified in Figure 4.3. The quantification of the following deterministic nodes is discussed:

- Pedalling power
- Walking speed

[18] The scope of the indicator stated in Section 4.2 requires the ability to compare base case indicator values between areas.

- Time budget physical constraint
- Time budget social constraint
- Bicycle characteristics
- Effect of topography on effort, pedalling power and walking speed

The quantification of the other deterministic nodes: slope, wind speed and circuity are discussed in Chapters 6 and 7.

5.7.1 Comparison of methods to estimate pedalling power

Pedalling power in this context means the rate of useful work applied to moving the cranks to propel the bicycle (as defined in Table 4.1). When a person rides a bike they use energy in other ways too. Energy is used to run the metabolic systems of the body and to lift the legs against gravity to the top of the pedal stroke. Two pilot pedalling power models were tested and an improved model developed. However, the improved model still contains a number of simplifying assumptions.

5.7.1.1 Pedalling Power pilot model 1

Pilot pedalling power model 1 used the regression model shown in equation 5.6 to predict pedalling power. The regression model was developed from primary data by Keytel et al., (2005) based on a cohort of 105 people drawn from a fitness club and amateur running and cycling races to predict energy expenditure from heart rate monitoring during sub-maximal exercise. This took account of weight, gender and VO_{2max}[19]. It assumed that if a person was heavy, then that person had a lot of muscle, and was able to generate a lot of power. It did not assume heavy people were obese (presumably due to the nature of the test cohort). This may be reasonable if the population is a group of athletes or trained amateur cyclists, but it did not work when applied to the general population. When this model was applied to the general population using data from the Health Survey for England, obese people were given very high pedalling power values. As equation 5.6 and Table 5.14 show, excess weight in the form of body fat amongst obese people would erroneously increase the pedalling power available. Additionally Keytel et al's method takes no account of the effect of regular exercise which has an important influence on pedalling power (e.g. Cerretelli et al., 1975 and Farrell et al., 1993).

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[19] VO_{2max}(measured in ml kg of body weight per minute) is a measure of a person's maximum oxygen uptake. It is used as an indicator of cardio-vascular endurance and can also be used to calculate a person's energy use and power output during exercise (McArdle 2010).

Based on the description given Keytel et al, It is assumed that their term *EE* represents mean energy expenditure in Kilo Joules per minute during a 20 minute work-out using a treadmill or stationary bike. Though not specifically stated in their paper, their figure 1 on p290 uses this unit on the graph axes. This is not ideal because this is a non-standard expression for Watts. It would be clearer if Keytel et al had used SI units. The vagueness of the paper's reporting of units was a further reason for not using this method.

$$\begin{aligned}\mathrm{EE} = (&\mathrm{gender} \times ((-55.0969 + 0.6309 \times \text{heart rate}) + (0.1988 \times \text{weight}) \\ &+ (0{:}2017 \times \text{age})) + ((1 - \text{gender}) \\ &\times (-20.4022 + 0.4472 \times \text{heart rate}) - (0.1263 \times \text{weight}) \\ &+ (0{:}074 \times \text{age}))\end{aligned}$$

[5.6] Source (Keytel et al., 2005 p293). Units: Age in years, heart rate in beats per minute, gender; male = 1 female = 0, weight in kg.

EE was converted into Watts. *EE* represents total energy consumed. A person on a bike works at an approximate efficiency of 20-30%; that means 20-30% of all energy consumed is applied as power through the cranks (Wilson, 2004). If an efficiency value of 0.25 is used then the Pedalling Power (PP) in Watts is:

$$PP = 0.25 \times \left(\frac{EE \times 1000}{60}\right)$$

[5.7]

An application of these equations and assumptions is given in Table 5.14. The values for EE (converted to Watts) and Pedalling Power found in the example in Table 5.14 are of the same order of magnitude as the values for metabolic heat and propulsive power quoted by (Wilson, 2004, p. 76) confirming EE is a measure of total power consumption not propulsive power output.

Table 5.14 A numerical example applying equation [5.6].

The values used in the table are the mean values for males using a cycle ergometer sourced from Keytel et al's paper in Table 1 p290

Note how the obese male is assumed to have a greater Pedalling Power output even though there is no evidence that they are more muscular or in possession of other advantage.

Independent variables	average male at 77% of max heart rate	obese male
Gender	1	1
Max HR	187	187
Heart rate (77% of maximum)	144.0	144.0
Weight (kg)	81	95
Age (years)	31	31
Dependent variable		
EE (total bodily energy expenditure Kilo Joules per minute)	58.1	60.9
Conversion of EE to Watts		
Power (total bodily power consumption Watts)	968.4	1014.8
conversion to Propulsive power assuming 25% efficiency		
Propulsive power W	242.1	253.7
Total energy consumption		
Assumed total energy usage during 20 minute workout described in the paper (KJ)	1162.0	1217.7

5.7.1.2 Pedalling Power pilot model 2

The second pilot model used an estimation based on the work of Jones and Poole, (2004); Pringle and Jones, (2002); Smith and Jones, (2001*)* and Whipp and Rossiter, 2005). Equations are given below. This second pilot model uses the concept of Lactate Threshold. Lactate is a by product of the conversion of fuel in the muscles into energy. Lactate Threshold (LT) is defined *as "the highest oxygen consumption or energy intensity achieved with less than a 1.0 milimole mM increase in blood lactate concentration above the pre-exercise level" (McArdle, 2007 p299).* Below Lactate Threshold there is very little accumulation of lactate, because any lactate produced is removed at the same rate. Exertion below and up to LT is regarded as 'highly sustainable'. Sport scientists work on the principle that a person's cardio-vascular system can work up to Lactate Threshold all day provided they take on suitable energy and liquid whilst they ride (McArdle, 2007).

Lactate Threshold (LT) is an important determinant of endurance for elite athletes, but it is also useful for modelling the cycling ability of the normal population. Exceeding LT means there is more lactate in the blood. For sedentary individuals unused to exercise, the result is a feeling of tiring muscles and greater effort which forces the rider to slow down or rest after a short period of time. Lactate Threshold limits exercise intensity. Fit recreational cyclists and other moderately trained amateur athletes can work at a higher rate of exertion for a period of time. Their limit on exertion is a higher lactate concentration referred to as the Onset of Blood Lactate Accumulation (OBLA). OBLA is defined as the point where blood lactate levels exceed 4.0mM/litre of blood (McArdle, 2007). In this “heavy exercise domain” the length of time individuals can work between LT and OBLA varies, but a suitable estimation for fit recreational cyclists and amateur athletes is approximately 2 hours per day with appropriate nutrition (McArdle, 2007).

Table 5.15 describes Lactate Threshold in terms of VO_{2max}. VO_{2max} is a measure of the ability of the body to take up and use oxygen to expend energy. VO_{2max} is used as a measure of cardio-vascular fitness. It can be reported in two ways: Firstly relative to body mass measured in ml of O_2 per kg of body mass per minute[20], and secondly as maximum oxygen uptake in ml of O_2 per minute (McArdle, 2010).

[20] For example Tour de France winner Greg Lemonde had a VO2max of 92.5 ml/kg/min (Wilmore and Costill, 2005). A fit male aged under 30 would expect a Vo2 max of ~ 52ml/kg/min. An unfit female over 60 may have a VO2max below 17ml/kg/min (Heyward, 2006).

Table 5.15 Exercise intensity domains

There are three exercise intensity domains. On the left of this table the approximate relationship is shown between the intensity domain and percentage of VO_{2max} (ml/kg/min). Table after Ferguson C, (pers comm. based on work of Jones and Poole, 2004; Pringle and Jones, 2002; Smith and Jones, 2001,Whipp and Rossiter, 2005) .

% of VO2max	Domain	Implication for exertion during commuting
75-100	Very heavy / maximum exertion above OBLA	Exertion at or close to VO_{2max}. Lab tests at this intensity tend to be between 2 and 30 minutes duration. This domain is too intense for commuting.
50-75	Heavy above LT and below OBLA	A fit recreational cyclist could work at this rate for up to 2 hours per day with a minimum 8 hours recovery and good nutrition, but not a sedentary individual. Only fit amateur athletes / cyclists can work in the heavy domain.
0-50	Sub –Lactate Threshold	This level of cardio- vascular exertion is sustainable for a non-athlete for several hours if there is no medical condition.
	Baseline exertion moving legs against gravity	This level of exercise is below LT for all but the most unfit.

Based on lab testing it is found that an oxygen uptake of 10ml/min produces in addition to powering metabolic processes a 1 Watt power output which can be used for lifting the legs or propelling the bike (Jones and Poole, 2004). This is the Rider Power Output (measured in Watts). This means that at a given instant:

$$\text{Rider Power Output in Watts} = \frac{\text{Total oxygen uptake}}{10}$$

[5.8]

The Rider Power Output has two components; the proportion used to lift the legs against gravity (the Baseline Power Requirement) and the proportion used to turn the pedals (Pedalling Power). From this, the Pedalling Power (in Watts) is calculated. For sedentary individuals a simplifying assumption is made that oxygen uptake at LT is half that at VO_{2max}.

This means that the Rider Output Power at LT is 0.5 x VO_{2max} in ml/kg/min x mass in kg. The Pedalling Power is the Rider Output Power minus the Baseline Power. $VO_{2Baseline}$ is the oxygen uptake in ml required for the Baseline Power. For simplicity in this pilot model $VO_{2Baseline}$ was set at 500ml equating to 50Watts of Rider Output Power based on the approximations in Table 5.14 and the equations above. This is a reasonable approximation for an 'average person' pedalling at 50-70 revs per minute (Jones and Poole, 2004). Pedalling Power was calculated as follows:

$$Pedalling\ Power\ = \frac{(0.5 * VO2max_{ml}) - VO2_{Baseline}}{10}$$

[5.9]

Example: A person has a maximum oxygen uptake $VO_{2max\ ml}$ of 3000ml/min

$$Pedalling\ Power\ = \frac{(0.5 * 3000_{ml}) - 500_{ml}}{10}$$

$$= 100W$$

[5.10]

The simplification of the $VO_{2Baseline}$ (ml) value does not take account of the fact that a person with heavier legs will require more energy to lift their legs against gravity before useful work to propel the bicycle (Pedalling Power) is applied through the cranks. This however may not make a large difference except amongst people carrying large amounts of excess weight on their legs. A more influential simplification in this pilot is that across the population there is variation in the percentage of VO_{2max} (ml/kg/min) at which an individual reaches Lactate Threshold. Jones and Poole (2004) state that LT may vary from 35% in patients to 80% in elite athletes. Particularly this second pilot model does not account for amateur athletes / fit recreational cyclists being able to work at higher rates for a period of time without risk of ill health or injury.

5.7.1.3 Improved model of Pedalling Power

The two previous models were not good enough because they did not take account of the following:

> Lactate Threshold is influenced by BMI: Pilot model 1 wrongly assumed that all increases in weight were associated with increased power, without considering obese individuals.
> Lactate Threshold is influenced by how often people exercise, which is not considered in the pilot models above.
> Maximum work rate above LT is possible for fit individuals for a limited period of time. This takes greater account of the range of fitness levels in the general population than pilot model 2.
> Work done moving legs against gravity depends on the size of the person. This is also not considered in the pilot models above.

An improved model was built to take some account of the following evidence. Amongst non athletes, there is evidence that BMI affects the percentage of VO_{2max} (ml/kg/min) at which people reach Lactate Threshold. Bircher and Knechtle, (2004) tested a group of sedentary obese[21] people finding a mean LT of 49.7% of VO_{2max} (ml/kg/min) for obese females and 47.9% for obese males. Kim et al., (1991) tested sedentary overweight women with a mean BMI of 26 $\pm$ 1.3 and their LT averages 54%. In addition, various exercise training websites (e.g. Davies, nd) cite LT for untrained normal weight people as 50 - 60% of VO_{2max} (ml/kg/min) based on references such as Cerretelli et al., (1975) and Farrell et al., (1993).

Increasing the amount of regular exercise is associated with an increase in Lactate Threshold. For example, Kim et al., (1991) report LT% rises by 16% after a 14 week training programme of vigorous exercise for overweight non-obese experiment participants. Based on the evidence the following simplifying assumptions were made: Obese individuals have a Lactate Threshold of 48%. Sedentary people with non-obese BMI have a LT of 50-55%; those who meet exercise guidelines have a LT of 55-60%. Those who do more than 180 minutes vigorous exercise per week are assumed to have a both a higher Lactate Threshold and the ability to work in the heavy domain for periods up to 2 hours per day. Elite endurance athletes are not considered in the model.

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[21] Obese is defined as a BMI over 30, overweight is BMI 26-30, normal weight is BMI 20-25
http://www.noo.org.uk/NOO_about_obesity/measurement

The second pilot model assumed that an average person required 500ml of oxygen per minute to generate the 50W needed for the Baseline Power Requirement (Jones and Poole, 2004) This was discussed in Section 5.7.1.2 (see equation 5.8). The oxygen required for the Baseline Power Requirement also accounts for the power consumed to run the body's metabolism. Metabolic power consumption is more closely related to fat free mass than total body mass (McArdle, 2007). This means that the metabolic power consumption of an obese and a non-obese person of the same age, gender and height will be similar. The implication for the current modelling process is that there will not be large increase in metabolic power consumption between obese and non-obese people who are otherwise physiologically similar.

There may be some differences in the power consumed lifting the legs during each pedal rotation. This figure will vary. In simple terms, heavier legs require more energy to be used before any bike propulsion is done (Lafortuna et al., 2006). If an 'average' person weighs 78kg and has a 50W Baseline Power Requirement, a simple estimation to take some account of the effect of obesity on the Baseline Power Requirement without wrongly assuming that excess fat increases metabolic power consumption is:

$$Baseline\ Power\ Requirement = \frac{BMI}{25}\ \times 50$$

[5.11]

A BMI of 25 represents the upper bound of a healthy weight so 25 is used as the denominator. The improved model showed an increase in the difference in Pedalling Power between obese sedentary individuals and normal weight individuals who exercised regularly. This greater variation in Pedalling Power better reflects the large variation in the population at large.

5.7.2 Walking speed

The uptake of oxygen increases with walking speed. This is shown in Figure 5.5. as being linear for a walking speeds between 1km/hr and 6km/hr. From the graph equation 5.11 can be derived.

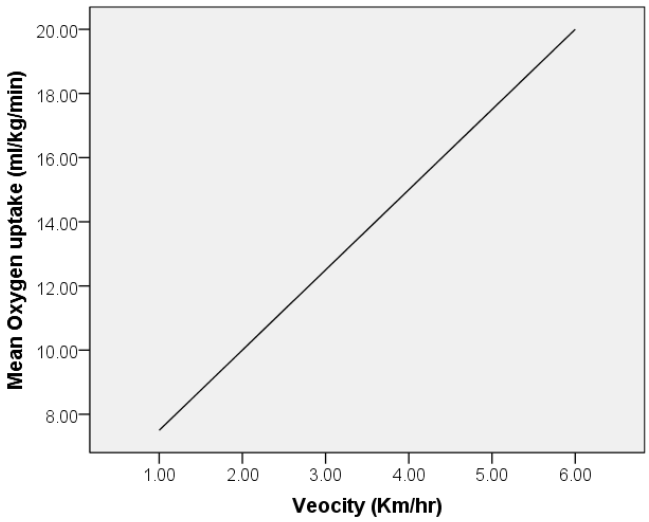

Figure 5.5 Oxygen uptake versus walking speed source (McArdle 2010)

A simple estimation is used for velocity V based on measurements carried out during testing reported in (McArdle, 2010). 2.5 is the slope of the line when walking at speeds between approximately 1km/hr and 6km/hr.

$$V = \frac{(0.5vo2\text{max}) - 5}{2.5}$$

[5.11]

An example based on this is as follows: The mean VO_{2max} (based on the Health Survey for England) is 36ml/kg/min. A VO_2 uptake of approx 18 ml/kg/min results in walking speed = 5.2 km/hr. For the “average” person this oxygen uptake is approximately 50% of VO_{2max}, which is below Lactate Threshold and below the heavy exercise intensity domain. The graph concurs with the long established Naismith’s rule: people walk on the flat at 3mph ~5km/hr (Naismith, 1892). It is acknowledged that equation 5.11 is simpler than that used to calculate cycle speed. It does not calculate the intermediate value walking power, because it does not account directly for Lactate Threshold as the Pedalling Power model does.

More complicated models could measure calories used based on weight, such as in a series of models building on Ralston, (1958). However, the increased complexity versus return in increased accuracy is low for this iteration of the model. Even more complex models such as those accounting for gait and leg length (e.g. Sprott, n.d.) are not practicable because of lack of data. This more complex model would be needed to account for the effect of BMI and lifting non-lean body mass in the legs with each step. A model of walking speed based on gait (Bohannon, 1997) was not used as it did not account for fitness.

5.7.3 Determining time budget

As explained in Section 4.3 the time budget has both a social and a physical constraint.

5.7.3.1 Physical constraint

The *physical constraint* on time budget is determined by the body's system of muscles and joints. Any individual who is not already a regular cyclist may be affected by saddle soreness, muscular and joint pain. There is some evidence to suggest that after riding for two hours even many experienced riders would express discomfort when using a normal bicycle saddle (Keytel and Noakes, 2002). Discomfort is likely to be felt sooner by those beginning cycling. Christiaans and Bremner, (1998) reported that almost 60% of 453 Dutch volunteers testing cycling comfort complained of soreness of some type when riding their own bicycles on journeys of less than one hour's duration. One hour would seem to be an upper limit for the general population (the majority of whom are sedentary and not regular cyclists) so that the effect of aches and pains would not be compounded over several days leading to injury. The physical constraint assumes that individuals would be physiologically capable of travelling to work and back five days per week without injury. Mobility and disability is also considered part of the physical constraint. This could be modelled explicitly, or taken account of in the spatial microsimulation process by making use of census attributes for Limiting Long Term Illness. The latter approach is less complicated as it takes general account of illness and disability rather than trying to model the implication of specific conditions.

5.7.3.2 Social constraint

The physical constraint determines a maximum travel time. The need to make escort trips could further reduce the time available for commuting. A simple approach to quantifying this effect is to assume that all people who need to escort children have to reduce their commute time by a set amount. The simplifying assumption is made that the time cost is 30 minutes.

The rationale for this simplifying assumption is set out as follows: Firstly, a maximum travel distance by active modes (walking or cycling) had to be set. Prior to modelling the mean maximum distance for individuals, only rough estimates of maximum commute distance are available; 8km for cycling and 5km for walking giving a mean maximum commute distance of 6.5km.

These rough estimates are criticised in Section 4.3.1. The mean maximum distance by active modes is used as a simple proxy for commute distance. The analysis uses this figure as it represents individuals in the population who would be likely to be able to commute by active modes if they do not have to include an escort trip. Though the UK National Travel Survey Table NTS 0405 (DfT, 2010a) states that the mean commute distance in the UK is approximately 14km, this was not used because this is well beyond the walking or cycling capability of most people. Most people would be unable to commute this distance even if they do not have to include an escort trip. Once the commute distance was set, the distance to child care was set as the mean escort education trip distance taken from the UK National Travel Survey Table NTS 0405 (DfT, 2010a).

When both the commute and the escort trip are in the same direction, there is no time penalty to the trip. If the escort trip is not in the same direction as the commute trip, the overall journey to work increases in distance and a time penalty is incurred. Table 5.16 shows the results of a simple geometric analysis. The estimated mean time penalty of having to include an escort trip as part of the commute is 20 minutes.

However mean maximum commute distance by walking and cycling do not account for hilliness, so the figure is likely to be lower than 6.5km. If distance to work decreases relative to distance to child care, the time cost of including an escort trip will increase. For this reason 30 minutes is chosen as the simplifying assumption of the time cost of escort trips.

Alternative means of calculating the social constraint were considered, but were rejected on the basis that it is unlikely that suitable data would be available this would lead to more assumptions to be made without any gain in accuracy.

Table 5.16 Results of geometric analysis assessing the time cost of having to make escort trips as part of a commute by walking or cycling.

Direction of school relative to direction to work	**Distance home to child care**	**Distance child care to work**	**Total distance**	**Direct distance home to work**	**Ratio, distance home to work / total distance**	**Time penalty of escort trip (minutes)**
no diversion	3.68	2.82	6.50	6.50	1.00	0.00
school at 45^0	3.68	3.88	7.57	6.50	0.86	8.46
school at 90^0	3.68	7.47	11.16	6.50	0.58	25.04
school at 135^0	3.68	7.18	10.87	6.50	0.60	24.11
school opposite direction 180^0	3.68	10.18	13.87	6.50	0.47	31.88
school at 225^0	3.68	10.02	13.70	6.50	0.47	31.54
school at 270^0	3.68	7.47	11.16	6.50	0.58	25.04
school at 315^0	3.68	4.49	8.17	6.50	0.80	12.27
				average	**0.67**	**20.00**

One alternative method would be to calculate the distance from each zone to the nearest school. In the UK, the Index of Multiple Deprivation data includes an estimate of distance to the nearest primary school along the road network (McLennan, 2011). However this data is not produced at the finest resolution (it is available at Lower Super Output Area resolution not Output Area resolution). The UK government produces accessibility data and statistics estimating the proportion of people who could access their nearest school using different modes including walking and cycling (DfT, 2012). The flaws in using this data for this research are that firstly, the assumption is made that all people access their nearest facility. Secondly, the accessibility measures also do not consider travel to child care locations for pre-school children. Thirdly, the measure lacks consideration of the capacity of individuals to travel by active modes. As discussed in Section 3.1.3 the DfT accessibility measures do not explicitly consider physical capacity and effort when travelling by active modes.

Another more complex method would be to gather data on the relationship between commute distance and escort trip length. There is some suggestion that the length of escort education trips are related to commute distance. An initial examination of the UK National Travel Survey (NTS) individual data from 2002 – 2014 showed a moderate correlation between escort education trips and commute distance where commute distance is under 6km. Above 6km there was little correlation. However, this information would only be useful if the data is available for the actual origin, school location and work location. This is because for one adult the school is on the route to work so there is no diversion and the departure time is suitable for both parent and child. However for another adult, school is in the opposite direction to work and departure times are not compatible for parent and child. To address all these issues fully would require data that is unlikely to be available for this research.

5.7.4 Bicycle characteristics

Heavy bicycles increase the amount of effort required to ride up hill. On the flat, bicycle weight has relatively little effect. However bike weight is usually much smaller than rider weight so bike weight is less important than rider weight. The rolling resistance of bicycle tyres has a marked effect on the effort required to travel at a given speed. The aerodynamic position of the rider offered by different types of bicycle has significant effects at higher speeds. Whilst this is hugely important to racing cyclists, it is less important to non-athlete members of the general population who immediately after a fuel shock may be unused to commuting by bike. The proportion of power required to overcome rolling resistance and the proportion to overcome air resistance is estimated using calculations available from (Wilson, 2004). This is shown in Table 5.17 for speeds upto 10m/s. The mean Pedalling Power for all working individuals is estimated at 62 Watts. Table 5.17 shows that at this power output the speed of the bicycle is approximately 16km/hr (4.5m/s), friction and air resistance have similar importance. Note that at 25km/hr (~7m/s) which is often regarded as the '*design speed*' or 'commuting pace' *for regular cyclists* (Scottish Executive, 1999; TfL, 2005), air resistance exerts considerably more influence (~70% of power requirement) and the total power required is more than double. It is important for this indicator to be based on values relating to the population as a whole, many of whom may not be regular or experienced cyclists with the associated levels of fitness. It should not be based on design speeds related to the current behaviour of a small proportion of the population who currently commute regularly.

Mechanical efficiency for a well maintained bicycle is estimated at ~95% (Wilson, 2004). For poorly maintained or low quality bicycles this figure may fall to below 70% requiring a power input of 90W to travel at 4.5m/s. If data are available about the bike fleet and the spatial distribution of that fleet then this factor should be considered. The practicalities of doing so are discussed in Chapter 8. However if data regarding the distribution of the bike fleet are not available the simplifying assumption that bikes are 95% efficient is justified because it is at least consistent with the work of others (see for example Parkin, 2008; Parkin and Rotheram, 2010).

Table 5.17 The proportion of power required to overcome rolling resistance and the proportion to overcome air resistance on a utility bike on the flat.

Note changes in mechanical efficiency do not affect the relative proportions of power required.

Speed m/s	Power to overcome friction	Power to overcome drag	% of power to overcome friction	% of power to overcome drag	Total power required
0.0	0.0	0.0	0.0	0.0	0.0
0.5	4.0	0.0	99.0	1.0	4.0
1.0	8.0	0.3	96.0	4.0	8.3
1.5	12.0	1.1	91.5	8.5	13.1
2.0	16.0	2.7	85.7	14.3	18.7
2.5	20.0	5.2	79.4	20.6	25.2
3.0	24.0	9.0	72.8	27.2	33.0
3.5	28.0	14.3	66.3	33.7	42.3
4.0	32.0	21.3	60.0	40.0	53.3
4.5	36.0	30.3	54.3	45.7	66.3
5.0	40.0	41.6	49.0	51.0	81.6
5.5	44.0	55.3	44.3	55.7	99.3
6.0	48.0	71.9	40.1	59.9	119.9
6.5	52.0	91.4	36.3	63.7	143.4
7.0	56.0	114.1	32.9	67.1	170.1
7.5	60.0	140.3	30.0	70.0	200.3
8.0	64.0	170.3	27.3	72.7	234.3
8.5	68.0	204.3	25.0	75.0	272.3
9.0	72.0	242.5	22.9	77.1	314.5
9.5	76.0	285.2	21.0	79.0	361.2
10.0	80.0	332.6	19.4	80.6	412.6

In the absence of bike fleet data further simplifying assumptions can be made that the characteristics of a utility bicycle are reasonably representative of bikes available for commuting. The effects of bicycle characteristics on bicycle speed are summarised in Table 5.18.

Table 5.18 The effect of bicycle characteristics on bicycle speed.

For a bike rider weighing 80kg with a Pedalling Power of 81w. Speed in km/hr. (a) the effect of gradient, (b) the effect of tyres, (c) the effect of aerodynamic position.

(a)

Bike weight	Speed on flat	Speed at 4% grade
10kg	18.1	6.1
15kg	18	6.3

(b)

Tyres	Speed on flat
Mountain bike	14
Road slicks	22

(c)

Aerodynamic position	Speed on flat
Sit up / flat handlebars	18
Drop handlebars	20

5.7.5 The effect of topography on physical effort

The topography of an area is an important determinant of the maximum distance people could cycle [22]. Different hypotheses of how people choose to expend energy when cycling uphill, or accelerating after stopping, are available (Parkin, 2008; Graham, 1998); for example people's motivation may lead them to work at higher rates to maintain speed. Working above the rate which is sustainable for the whole journey might reduce the ability of

[22] Calculation of the gradient and the slope profile are dealt with in Chapter 7

people to be able to cycle for the whole of their time budget, or to recover and repeat trips.

The following simplifying assumptions are adopted. Firstly it is assumed that cyclists do not have to stop at junctions because following the fuel shock there is no motorised transport. The second assumption is that when riding uphill, people can maintain a constant rate of Pedalling Power (at Lactate Threshold for sedentary individuals and heavy exertion for the fittest individuals). The effect of this simplifying assumption is that people will ride slower up hill. Working above the rate which is sustainable for the whole journey might reduce the ability of people to be able to cycle for the whole of their time budget, or to recover and repeat trips. This simplification was within the scope of the indicator design – people should be able to make journeys without risk of injury caused by over exertion.

6 Methods used to construct the indicator

6.1 Introduction

Chapter 6 describes the modelling process used to estimate a new spatially explicit transport policy indicator which shows: Who could get to work tomorrow by walking and cycling if there was a fuel shock today? Chapter 6 builds on Chapters 4 and 5. Chapter 4 gave a rationale for the indicator scope (Section 4.2) and a conceptual indicator design (Section 4.3). Chapter 5 discussed methods which could be used to implement the conceptual design. In Chapter 5 it was found that the modelling process requires attributes of individuals as inputs (Section 5.2). Spatial microsimulation was chosen as the method to generate the individual attributes needed in the modelling process (Section 5.3). The specific technique adopted involves creating the synthetic population in two stages using a hybrid of spatial microsimulation techniques. The first stage uses a sample population and constraint tables with Simulated Annealing based software (Section 5.4). The second stage adds attributes not available in the sample population using Monte-Carlo sampling (Section 5.4). From these generated attributes an estimate of the indicator is made for each individual. Chapter 5 also discussed techniques to derive the following model variables from individual attributes: Pedalling power, walking speed and the physical and social constraints of time budget (Section 5.7). Following the design and discussion of methods which could be used, what is required in Chapter 6 is to describe the modelling process in full.

Chapter 6 contributes to objective 2:

> *To develop a static spatial microsimulation based method of implementing, for large populations, a model of capacity to make journeys using only walking and cycling which can be used to generate indicator results.*

The Chapter is structured as follows: Section 6.2 gives an overview of the modelling process. Section 6.3 formally defines the indicator showing notation. Section 6.4 describes the steps in the spatial microsimulation and Section 6.5 describes how the comparison of the base case and policy case is carried out.

6.2 An overview of the modelling process.

The modelling process has three parts (shown in Figure 6.1):

Part 1: Spatial microsimulation
Part 2: Calculation of the base case indicator
Part 3: Calculation of the policy case indicator.

6.2.1 Part 1: Spatial microsimulation

The spatial microsimulation has two stages. Stage 1 uses Simulated Annealing based Combinatorial Optimisation. A sample population contains the attributes: VO_{2max}, BMI, level of vigorous exercise, weight, age and gender needed to calculate the indicator as well as constraint attributes. Stage 2 uses Monte-Carlo sampling to add two individual attributes which were not available in the sample population; bicycle availability and the need to escort children on the way to work. It also adds commute distance which is a geographically dependent attribute; it is only allocated once it is known where an individual lives.

6.2.2 Part 2: Calculation of the base case indicator.

The individual attributes generated in the spatial microsimulation are used to calculate pedalling power, walking speed and the social constraint on the time budget (these were referred to as deterministic nodes in Sections 4.3 and 5.7). This is done using the calculations described in Section 5.7. Along with the individual attributes and associated deterministic nodes, wind speed, slope, and bicycle characteristics are input to the model. The maximum distance an individual can travel is calculated and compared to their current commute distance. If the former is greater, the individual has the adaptive capacity to commute to work by walking or cycling following a fuel shock. The results for individuals are aggregated to give an indicator value for each zone.

6.2.3 Part 3: Calculation of the policy case indicator.

Individual attributes are altered as they would be by successful implementation of the policy. Deterministic nodes and maximum distance an individual can travel following the policy intervention are calculated and compared to their current commute distance. If the former is greater, the individual has the adaptive capacity to commute to work by walking or cycling following a fuel shock. The policy case indicator can be compared to the base case indicator. Note that to calculate the policy case the spatial microsimulation is not re-run. This is discussed further in Section 6.5.

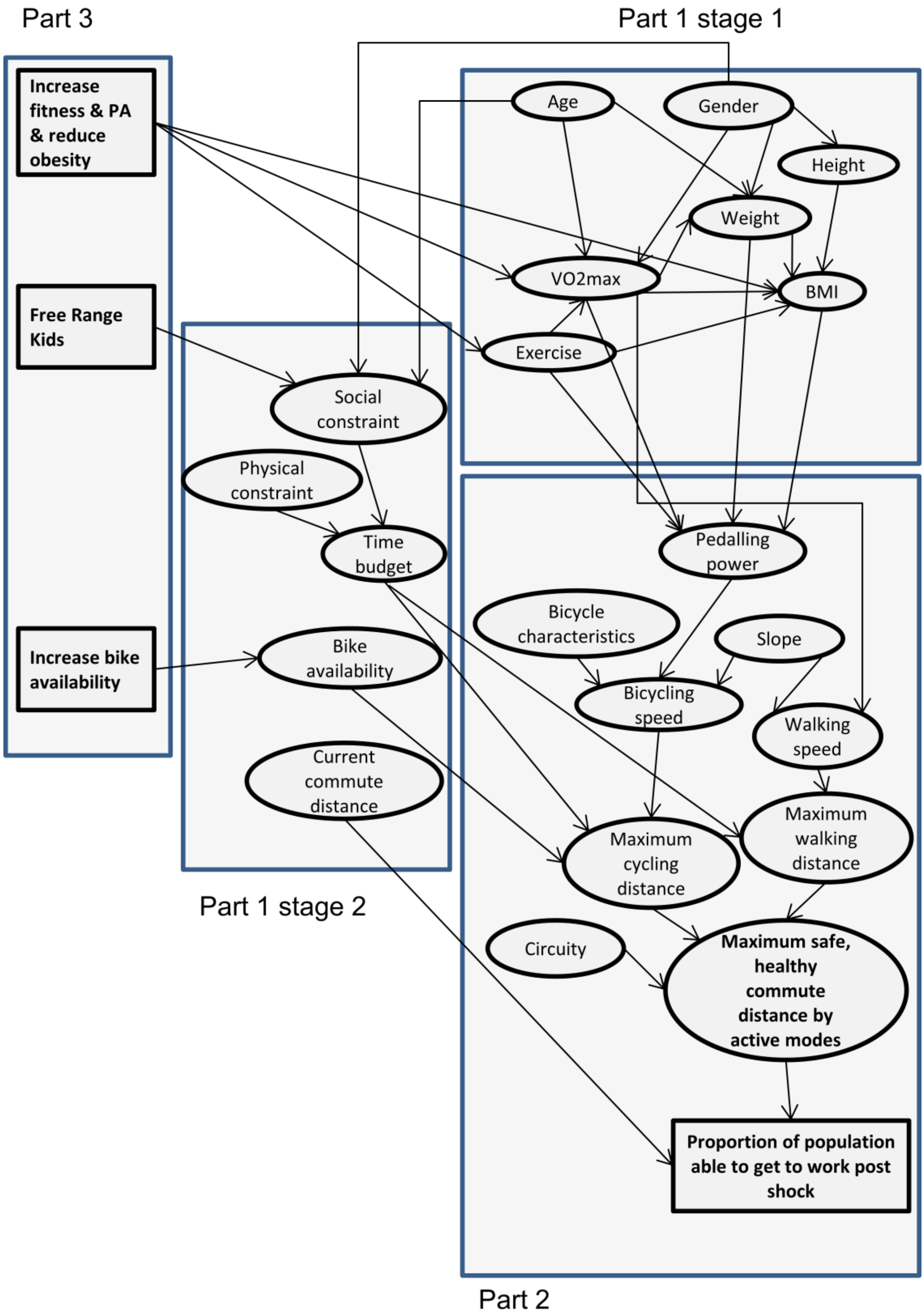

Figure 6.1 An overview of the modelling process

The boxes show the point in the modelling process where each attribute is input, calculated or output. The three parts to the modelling process are Part 1: Spatial microsimulation (with 2 stages); Part 2: Calculation of the base case indicator; Part 3: Calculation of the policy case indicator.

6.3 The Indicator: Definition and notation

The second part of the modelling process calculates the capacity of an individual to commute to their current workplace using only walking or cycling in a traffic network with no motor vehicles. The simple diagrammatic representation of the model is shown in Figure 6.2. It is a simplified version of Figure 4.3.

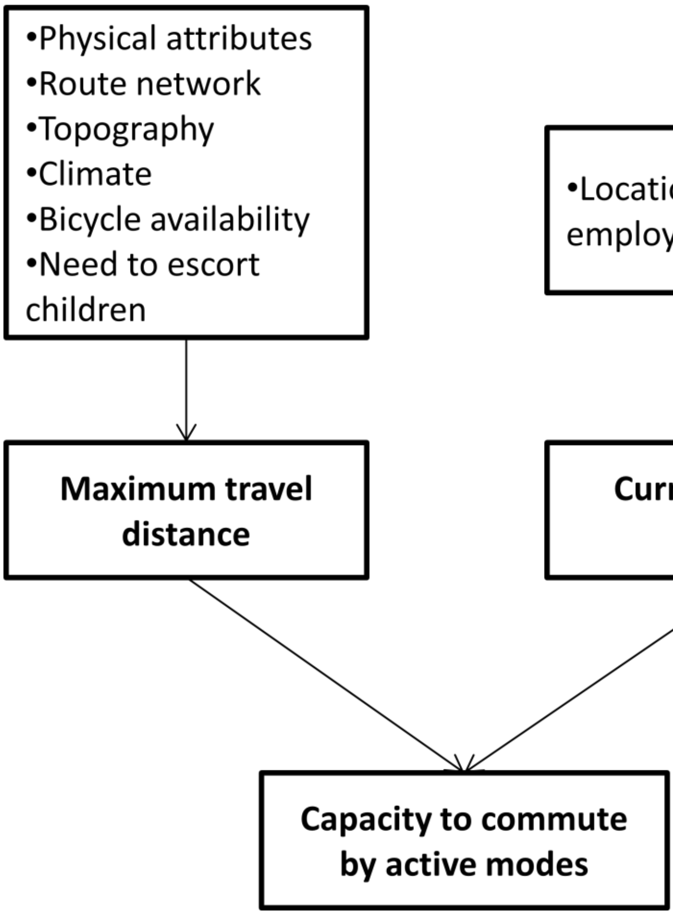

Figure 6.2 Simple diagrammatic representation of the modelling process required to calculate the indicator

This diagram is a simplified version of Figure 4.3.

All the people who are trying to commute are employed. For an employed individual *i* who lives in zone *j* their capacity to commute to their current workplace by walking and cycling A_{ij} is 1 if their maximum travel distance by active modes s_{ij}^{active} is greater than or equal to their commute distance C_{ij}.

$$A_{ij} \;=\; \begin{cases} 1 & s_{ij}^{active} \geq C \\ 0 & s_{ij}^{active} < C \end{cases}$$

[6.1]

The model output is given as an aggregation of the individual measure in [6.1]. This model output is reported as an indicator of the adaptive capacity of people to fuel shocks. All the people who are trying to commute are employed. The proportion of employed people living in zone *j* who can commute is $A_{j.}$ The sum of those who can commute is divided by the employed population of zone *j*.

$$A_j = \frac{\sum A_{ij}}{employed\ population\ of\ zone\ j}$$

[6.2]

In Section 4.3, the factors influencing the model and the indicator were identified. Relationships between factors were identified in Figure 4.3 and can also be seen in Figure 6.1. The model described below quantifies the relationships between these factors.

6.3.1 Commute distance

The current commute distance for an individual derived from secondary data sources such as the UK census is measured as a Euclidean distance between origin and destination. The model requires this distance to be converted to a network distance. To account for circuity (the ratio of network distance to Euclidean distance), the Euclidean commute distance X_{ij} is multiplied by a circuity factor *z*. The circuity factor depends upon the case study area and is discussed further in Chapter 7.

$$C_{ij} \;=\; X_{ij} \;\times z$$

[6.3]

6.3.2 Maximum distance by active modes

If the maximum travel distance by bike s_{ij}^{bike} and by walking s_{ij}^{walk} have been calculated, the availability of bicycles are assigned probabilistically for each individual. Each individual has a probability of having a bike. If only a national average value for bike availability is available, the probability is the same for all individuals. However if data is available giving the proportion of individuals from different segments of the population who have access to a bike, the probability is different for each population segment $p_{segment}$. The probability of having a bike determines s_{ij}^{active}. The simplifying assumption can be made that if a person has a bike they have the capacity to use it and does so. However, the applicability of this assumption should be checked when building an indicator using case study data. In the following circumstance the indicator value may be affected: Where the maximum cycling distance is smaller than the maximum walking distance, and the maximum walking distance is greater than the maximum commute distance. In this case, there is a danger that some individuals may be wrongly assumed not to have adaptive capacity.

To avoid this problem, the maximum travel distance can be estimated as follows:

$$s_{ij}^{active} = \begin{cases} s_{ij}^{bike} & with\ probability\ p_{segment}\ and\ s_{ij}^{bike} \geq s_{ij}^{walk} \\ s_{ij}^{walk} & with\ probability\ p_{segment}\ and\ s_{ij}^{bike} < s_{ij}^{walk} \\ s_{ij}^{walk} & otherwise \end{cases}$$

[6.4a]

One could assume that if an individual has a short commute of under a mile (1.602km), and has capacity to either walk or cycle, even if that person has access to a bike they are likely to walk. This assumption is based on data such as Table NTS0309 of the UK National Travel Survey (DfT, 2010a). Equation 6.4a could be modified to give:

$$s_{ij}^{active} = \begin{cases} s_{ij}^{bike} & with\ probability\ p_{segment}\ and\ s_{ij}^{bike} \geq s_{ij}^{walk}\ and\ Cij > 1.602 \\ s_{ij}^{walk} & with\ probability\ p_{segment}\ and\ s_{ij}^{bike} < s_{ij}^{walk} \\ s_{ij}^{walk} & otherwise \end{cases}$$

[6.4b]

Equations 6.4a and 6.4b do not produce different indicator results. 6.4b does however introduce speculation about human behaviour after a shock. For consistency, equation 6.4a is used in this thesis.

Maximum cycle distance s_{ij}^{bike} is calculated in km. It is equal to the velocity of the bike in km/hr V_{ij}^{bike} multiplied by time budget in minutes t_{ij}. As a result:

$$s_{ij}^{bike} = v_{ij}^{bike} \times t_{ij}$$

[6.5a]

Walking speed in km/hr V_{ij}^{walk} is calculated using the approximation based on %VO_{2max}(ml/kg/min) whilst walking from McArdle,(2010) and time taken to ascend whilst walking based on Naismith,(1892). This was explained in Section 5.7.2

$$s_{ij}^{walk} = v_{ij}^{walk} \times t_{ij}$$

[6.5b]

The time budget t_{ij} is dealt with in equation [6.6], then the calculation of velocity V in equations [6.7] – [12]. Time budget has a physical component P and a social component γ. The physical component is the maximum time it is physically reasonable to expect a person to be walking or cycling without risk of injury given the circumstances of the fuel shock. The circumstances of the fuel shock means that an individual who is not a regular walker or cyclist is assumed to have to start walking / cycling twice per day five days per week on top of carrying out work and domestic tasks. The social constraint is the reduction in time available for commuting if children have to be escorted. Section 5.7 discussed evidence that justifies a physical constraint of 60 minutes. The time cost of escorting children is a simplifying assumption and set at 30 minutes (this was also explained in Section 5.7). As a result:

$$t_{ij} = \begin{cases} 30 & \textit{if children have to be escorted on the way to work} \\ 60 & \textit{otherwise} \end{cases}$$

[6.6]

The calculation of velocity for cyclists is explained below in equations [6.7] – [6.12]. As explained in Section 5.7, the individual attribute pedalling power W_i is derived from other individual attributes; VO_{2max} ; the maximum oxygen uptake per minute (mlmin) O_i; Percentage of VO_{2max} at which Lactate Threshold (or upper working threshold in the heavy exercise domain for the fittest individuals) is reached l_i and Baseline Power b_i. This was discussed in Section 5.7.

$$W_i = \frac{O_i \times l_i}{10} - b_i$$

[6.7]

The upper threshold at which individuals can work (Lactate Threshold for most individuals) is related to Body Mass Index (BMI) and the number of minutes of vigorous exercise per week q (Bircher and Knechtle, 2004; Kim et al., 1991). The upper threshold l_i is allocated probabilistically. This is because as explained in Section 5.7 the upper threshold at which individuals can work varies between individuals. If a person has a BMI of over 30 then it is assumed they have an upper threshold of 48% of their VO_{2max} (ml/kg body mass/min). If they are overweight (BMI between 25 and 30) and they do less than 75 minutes vigorous exercise per week their upper threshold l_i is between 50-and 60% of VO_{2max} . A uniform distribution is used when drawing the value of l_i. This is because the literature examined stated the range of values 50 – 60 rather than a single most common value. The threshold value for normal weight individuals and those exercising more frequently are set in the same way:

$$l_i = \begin{cases} 0.48 & BMI > 30 \\ 0.5 - .06 & 30 > BMI > 25 \; and \; q < 75 \\ 0.5 - 0.6 & 20 > BMI < 25 \; and \; q < 75 \\ 0.5 - 0.65 & BMI < 30 \; and \; 75 < q < 180 \\ 0.55 - 0.85 & 20 < BMI < 25 \; and \; q > 180 \end{cases}$$

[6.8]

Resistance free work b_i is the power required to lift limbs against gravity during a pedalling rotation.

$$b_i = \frac{BMI_i}{25} \times 50$$

[6.9]

Velocity V_i has a cubic relationship with pedalling power W_i. V_i can be expressed in terms of pedalling power (Wilson, 2004). The individual attributes are: W_i= Pedal Power, V_i = bicycle velocity, m_i = mass of bike and rider are attributes of individuals. Θ is the slope %, and h_i the headwind in m/s characteristics of each zone. The values in Table 6.1 are assumed constant to simplify the model using values used in (Wilson 2004 p139 see Table 6.1). These are applied to equation 6.10.

Table 6.1 Constants used in the calculation of bicycle velocity

Constant	**Suggested value (after Wilson 2004)**
g=acceleration due to gravity	9.8 ms^{-2}
r=coefficient of rolling resistance	0.008
a= acceleration of the bike	0[23]
w= the effective rotational mass of the wheels	n/a
η= the mechanical efficiency of the bicycle	0.95
D=aerodynamic drag coefficient	1.2
A=frontal area of rider and machine	$0.5m^2$
ρ=density of air (kg/m^3)	$1.226kg/m^3$

$$W = \frac{V}{\eta}\left\{mg\left(r + \frac{\Theta}{100} + \frac{a}{g}\left[1 + \frac{w}{m}\right]\right)\right\} + \frac{V}{\eta}\{0.5DA\rho(V+h)^2\}$$

[6.10]

Equation 6.10 is rearranged in terms of *V* so the real root of the cubic can be found using the cubic formula. Alpha and beta are used in the cubic root formula:

Let

$$\alpha = \frac{mg\left(r + \frac{\Theta}{100} + \frac{a}{g}\left[1 + \frac{w}{m}\right]\right)}{\eta}$$

[6.11]

[23] A simplifying assumption of the modelling process introduced in Section 5.7.5 is that bicycles do not have to stop at junctions thus avoiding the need to accelerate back to cruising speed.

Beta is set at 0.385 when using the constants above. Alpha and Beta can then be used as inputs to the cubic root formula in the format $y = a\,x^3 + b\,x^2 + cx + d$. The parameters *a, b, c, d* are used in the cubic root formula[24]. Equation [6.12] also accounts for wind speed *h*.

$$f(V) = \overset{\boxed{a}}{\alpha} V^3 + \underset{\boxed{b}}{\beta}\,(V + h)^2 + V\underset{\boxed{c}}{(\alpha + \beta h^2)} - \overset{\boxed{d}}{W} = 0.$$

[6.12]

The velocity is calculated for going uphill, flat and downhill. An assumption has to be made about the slope profile. The simplest assumption is that all journeys have an uphill leg and a downhill leg. The maximum distance is based on the uphill leg. In reality few journeys are entirely up or down hill, so each application of the model should decide upon assumptions about slope profile. This is related to the data available and the case study areas so is covered in detail in Section 7.3.6

6.4 Modelling process part 1: Spatial microsimulation

The spatial microsimulation used the two stage hybrid of Combinatorial Optimisation and Synthetic Reconstruction techniques introduced in Section 5.6 The first stage uses Combinatorial Optimisation (in this case based on Simulated Annealing) to generate individual attributes. The assumption is that the case study data includes a sample of micro-data on individuals which contains most of the required attributes. The other input tables to this stage are constraint tables of small area aggregate counts. The second stage uses Monte-Carlo sampling to allocate gradient and commute distance. These attributes are geographically dependent so cannot be allocated from an aspatial national sample of individuals. Monte-Carlo sampling is also used to add any individual attribute which is not contained in the sample population. This makes the modelling process more

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[24] http://www.math.vanderbilt.edu/~schectex/courses/cubic/.

http://en.wikipedia.org/wiki/Cube_root

adaptable. The indicator can be estimated in different countries where the micro-data availability will differ.

6.4.1 Spatial microsimulation stage 1

As explained in Section 5.4, the sample population contains two types of attributes; firstly those which are common to both the sample population and the aggregate data. These attributes are candidates to be constraints (examples are given in Table 6.2). The second type of attributes are those found only in the sample population - unconstrained attributes. The choice of constraint attributes is based on those which are most strongly associated with the unconstrained attributes. The unconstrained attributes are listed in Table 6.3 alongside candidate constraint attributes with which they have a strong association.

Table 6.2 Attributes likely to be available as constraints

These are individual attributes likely to be found in the national census of OECD countries as well as in large scale surveys such as health and social attitude surveys. Because they are common to both surveys and the census, they are suiTable as constraints.

Attribute
Gender
Age
Education
Limiting long term illness
Economic activity
Socio-economic classification

Table 6.3 Attributes likely only to be available in a sample population

The attributes on the left are unconstrained attributes. They are typically not recorded as part of a national census.

Unconstrained Attributes of interest needed to calculate indicator	**Variables likely to be found in a national census which correlate to the attributes of interest**
Pedal Power	Age, gender, education, socio-economic classification, limiting illness

Height	Gender
Weight	Age, gender, education, socio-economic classification
BMI	Age, gender, education, socio-economic classification
Minutes of vigorous activity per week.	Age, gender, education, socio-economic classification.

Stage 1 of the spatial microsimulation was carried out using FMF(Flexible Modelling Framework) open source software which uses Simulated Annealing Combinatorial Optimisation to allocate individuals to the synthetic population by zone[25]. The data are prepared as shown in Tables 6.4 and 6.5. These tables are generic examples which could be built in different countries depending on the data available. The table structure used in the case study is shown in Chapter 7. Table 6.6 shows the format of the output from stage 1 of the spatial microsimulation.

Table 6.4 A generic sample population table

This is simplified. The sample population will typically have between 3 and 8 constraints.

Sample population		
Person id	Attribute 1 category	Attribute 2 category

Table 6.5 A generic constraint table

This is simplified. A constraint table may have more categories. There is a separate table for each constraint.

Constraint table for attribute 1		
Zone id	Count of people with attribute 1 category A	Count of people with attribute 1 category B

[25] The software and instruction manual are available at: https://github.com/MassAtLeeds/FMF

Table 6.6 The format of the output from stage 1 of the spatial microsimulation.

The person id can be used to link to all the individual attributes in a database

Output table	
Zone id	Person id

6.4.2 Spatial microsimulation Stage 2: Adding attributes by Monte-Carlo sampling

Adding an attribute which is not available in a sample population requires Monte-Carlo sampling. Let us assume that in an implementation of the modelling process, bicycle availability is not available in the sample population. Firstly an individual in the sample population needs to be given a probability of having access to a bicycle. An estimate of this value may come from another survey. For example it may be possible to derive the probability of having a bicycle given their age from a travel survey. A better estimate can be made if a cross tabulation in another table is available such as the probability of having access to a bike given age and gender. An even better estimate can be made if both demographic (age, gender) and socio-economic determinants of bike availability can be included. If a cross tabulation of the probability of bike availability given age, gender and socio-economic status is not available, then one is built using Iterative Proportional Fitting (IPF) as described in Chapter 5.4.2.1. Once the individuals in the sample population have been allocated a probability of having access to a bike, the Monte-Carlo sampling can determine which individuals have a bike (see Table 6.7).

Table 6.7 Adding an attribute which is not available in a sample population

Attribute 3 in draw 1 is allocated probabilistically. This step implements equation [6.4].

Adding attribute 3 draw 1			
Zone id	Person id	Probability of attribute 3	Attribute 3 in draw 1

Commute distance and gradient are geographically dependent. Gradient is an attribute of each zone. Gradient is simply added to the attribute list of each individual assigned to the zone. Commute distance is dependent upon individual attributes and the spatial location of the zone. A table of counts of the number of people in each zone travelling a particular distance band (e.g. 2-5km, 5 – 10km etc) is collected in a census. The table will be in a similar format to Table 6.8. A table of commute distances may only be available for the whole of the zone's population. However, if it is available by sub-group, for example commute distance by age and gender, then this is preferred. This is because it allows commute distance allocation based on both individual and geographic factors. With commute distance, IPF could be used to add another dimension to the cross tabulation. However, this is less important than with a variable like bicycle availability, because with the population having already being allocated to the zone by the stage 1 constraints, there is an inherent consideration of socio-economic factors.

Table 6.8 A commute distance table from a census

This is a generic table, but tables for the UK census follow a similar format

Count of individuals in each commute distance bin			
Zone id	Count of population with commute distance less than 2km	Count of population with commute distance less than 5km	Count of population with commute distance less than n km
All people			
Subgroup 1			
Subgroup 2			
…			
Subgroup n			

Table 6.9 Cumulative distribution table of commute distance by population subgroup

Subgroup 1 cumulative distribution table			
Zone id	Proportion of subgroup with commute distance less than 2km	Proportion of subgroup with commute distance less than 5km	Proportion of subgroup with commute distance less than n km

Table 6.10 Adding commute distance; an attribute which is geographically dependent

Adding commute distance draw 1			
Zone id	Person id	Population subgroup based on age and gender	Commute distance in draw 1

Using the steps above to populate Tables 6.7-6.10 multiple draws are made. Monte-Carlo sampling is used to generate multiple synthetic populations which form inputs to part 2 of the modelling process.

6.5 Modelling process part 2: Calculate the base case indicator

Each synthetic population is input to the modelling process. A_{ij} is calculated for every individual in every draw. The indicator value A_j is calculated for every zone in every draw producing a table similar to 6.11. As can be seen in Figure 6.4 (at the end of this chapter), the mean base case indicator value A_j over all draws is then calculated and is reported along with a measure of variation about that mean.

Table 6.11 Summary of indicator values for each zone over n draws

Zone id	Draw 1 A_j	Draw 2 A_j	Draw n A_j	Mean A_j over all draws	Standard deviation between draws

6.6 Modelling process part 3: comparison of base case and policy case

The third part of the modelling process compares the base case situation with the effects of doing specific policies (e.g. increase fitness; decrease obesity; increase bicycle availability). The attribute of the individual which would be affected by the policy is altered. The indicator value for each draw is recalculated and the mean across all draws is compared to the base case value. If the modelling process were rerun from scratch, then there would be stochastic differences between the base case and policy case populations. This would introduce stochastic noise and make it harder to discern policy effects (Rathi, 1992). To address this problem, an approach called ‘Common Random Numbers’ is used:

> *“CRN reduces stochastic noise between model runs and has the additional benefit of enabling modellers to conduct direct “counterfactual-like” analyses at an individual level.”(Stout and Goldie, 2008 p2)*

In this thesis, all of the data tables generated by the multiple draws are saved. This means that the Monte-Carlo sampling does not have to be re-run. The Common Random Numbers approach uses the same random number to simulate a specific attribute in both the base case and the policy case. The outcome is that individual *i* has a bike in both the base and policy case. This means that if a health policy is being tested, the change in the maximum travel distance of person *i* is entirely due to the policy and not due to “stochastic noise” (stochastic noise would be introduced if some individuals were given a bike in the base case and not in the policy case). This not only reduces computing time but more importantly it means that the base case synthetic population is not stochastically different to the policy case synthetic population. This allows smaller policy effects to be observed and still be statistically significant

6.7 Summary of methods used

This chapter has presented a description of the methods used to produce the synthetic population and calculate the model and the indicator. It is a generic method. It is not specific to one country and not dependent upon a particular survey with a particular set of micro-data attributes. Figure 6.1 showed the point at which attributes were input, calculated or output. The modelling process is also shown as a flow chart in Figure 6.4.

The methods can be applied anywhere where the attributes required by the model can be sourced in some form. The spatial microsimulation techniques described in Chapter 5 and above can be applied on something akin to a continuum depending on the format of data available as shown in Figure 6.3.

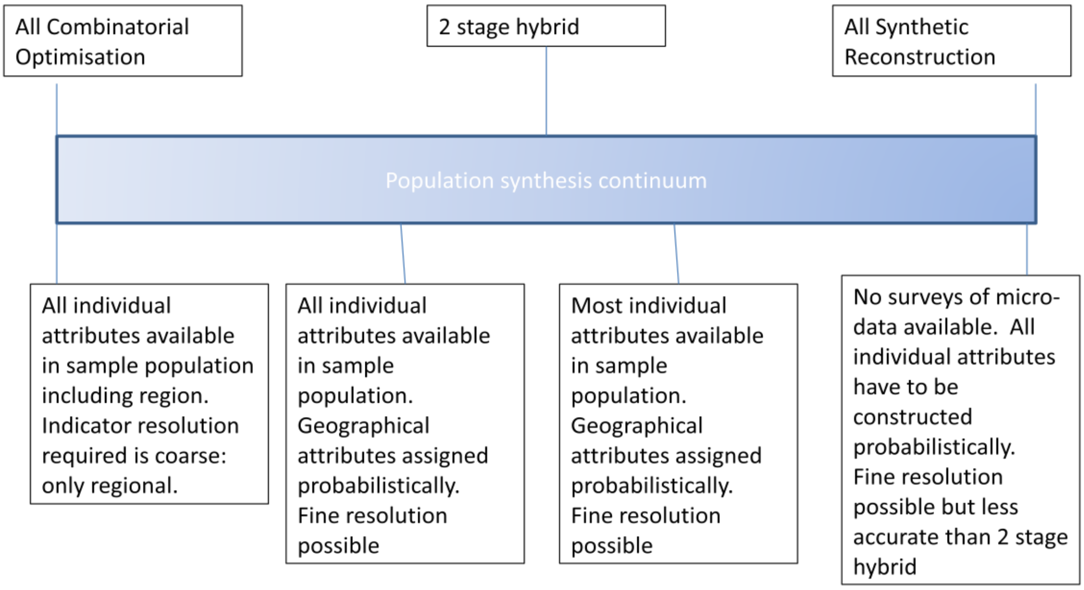


Figure 6.3 Spatial microsimulation continuum

The ability to apply the spatial microsimulation techniques differently to different data sets gives the method the flexibility to be applied in different countries.

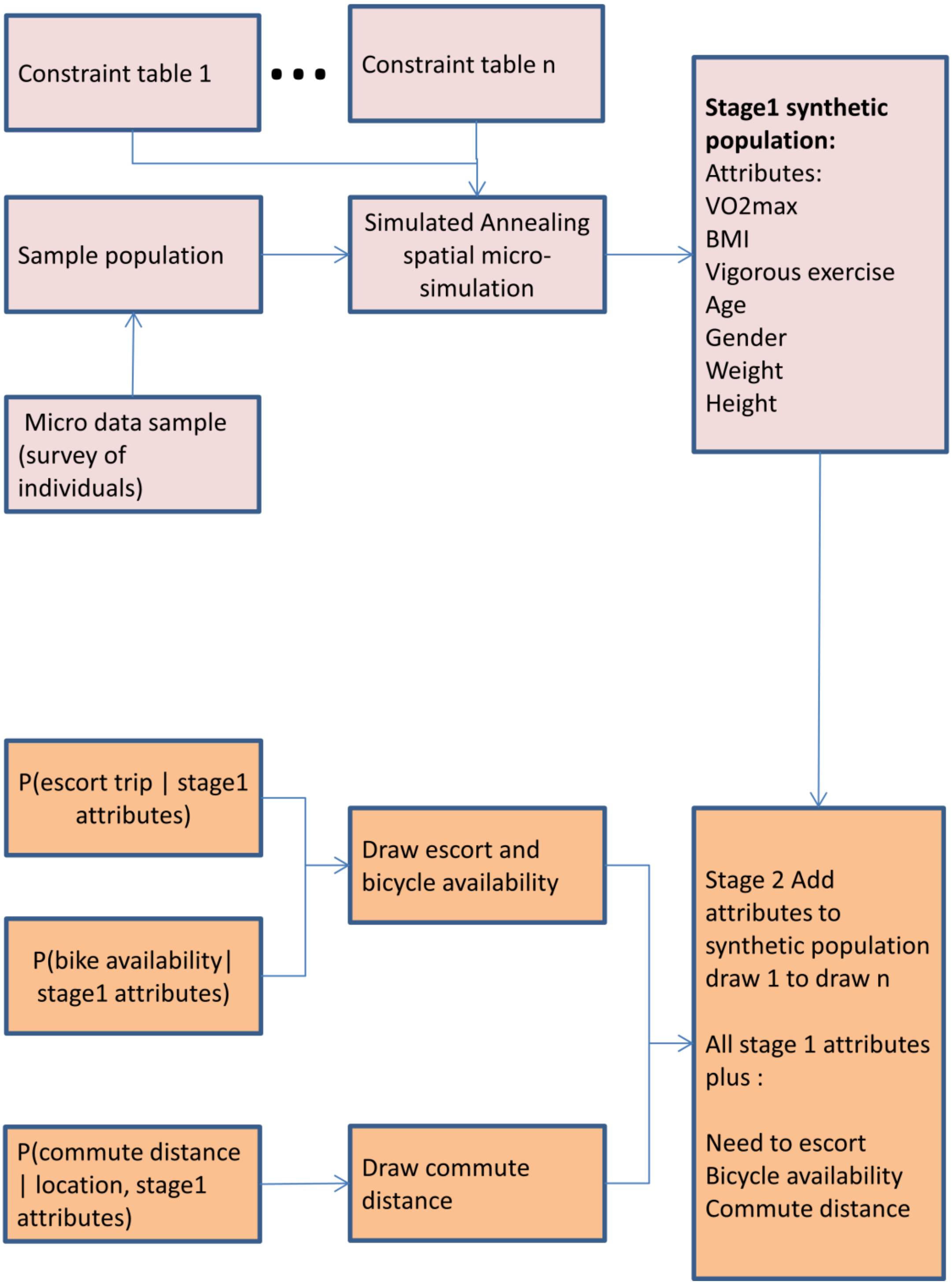


Figure 6.4a Steps in part 1 of the modelling process

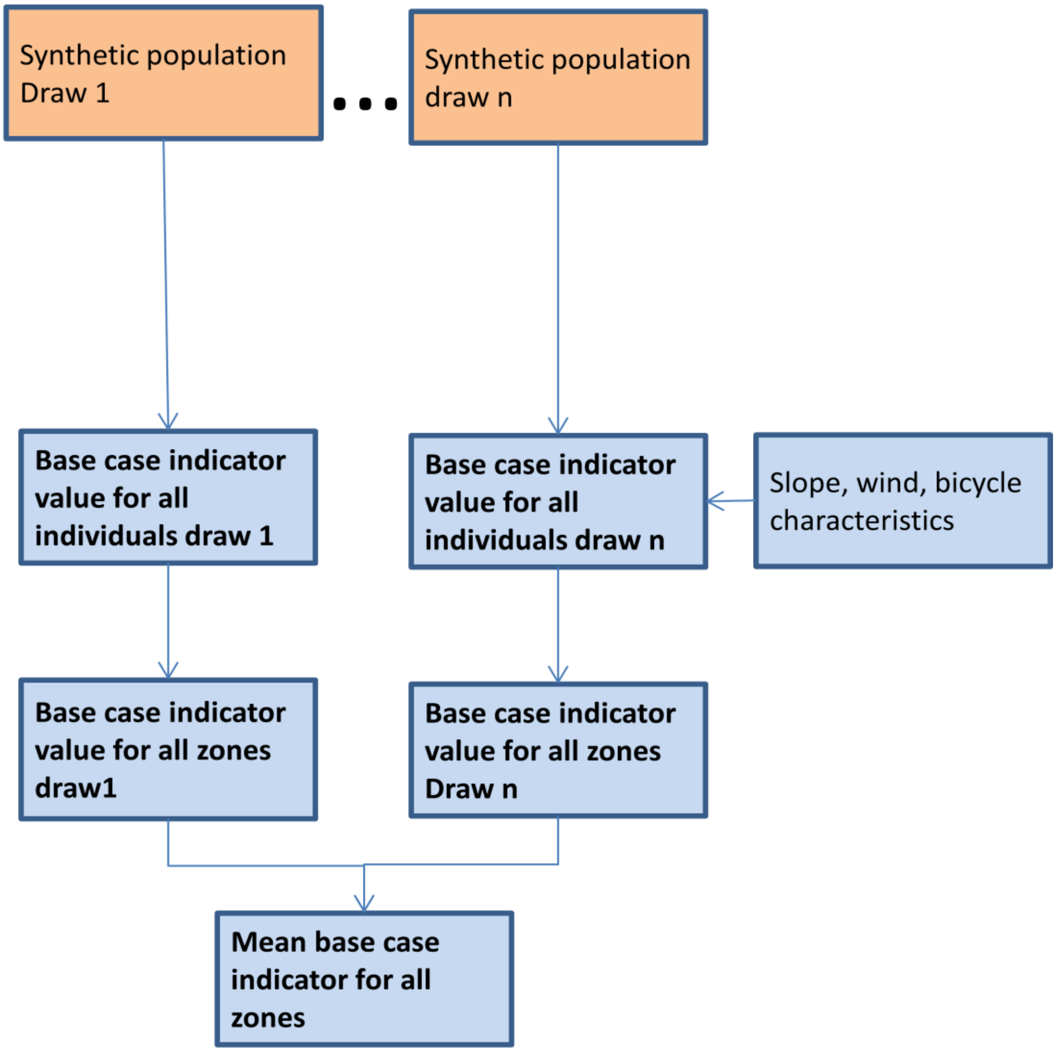


Figure 6.4b Steps in part 2 of the modelling process

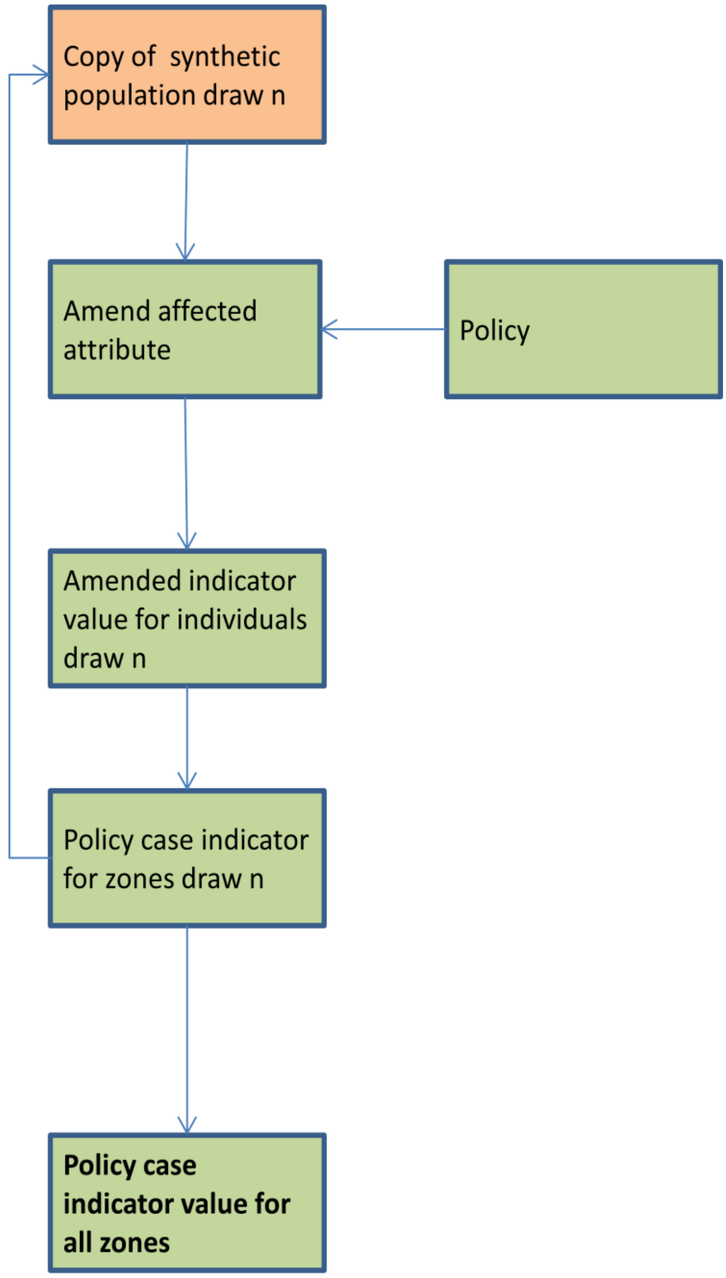


Figure 6.4c Steps in part 3 of the modelling process

Figure 6.4 Flow diagram showing the steps in the modelling process.

7 Data

7.1 Introduction

Data is required to apply the methods developed in Chapters 5 and 6. This chapter describes the data sources and data processing to apply the model to a case study which estimates the base case and policy case indicator values for the whole of England at a fine resolution. The choices made in selection of data sets and how they were processed is also discussed. The results produced are subject to the validation and sensitivity tests reported in Chapter 8. These tests inform the analysis of the policy relevant results presented in Chapter 9.

This chapter contributes to objective 3:

> *Objective 3: Test the applicability of the design and methods to real data. This will be achieved by integrating a range of secondary data sources from England to report results at both fine and coarser geographies (Output Areas[1] and coarser geographies in the UK hierarchy).*

The modelling process described in Chapter 6 requires as inputs the attributes of individuals plus data on bicycle characteristics, wind speed and gradient. The individual attribute data is generated using spatial microsimulation. The two basic data requirements of spatial microsimulation are firstly detailed data about individuals (such as a survey based on a nationally representative sample), and secondly aggregate data with fine resolution. This is usually the national census in both UK studies (Ballas et al., 2005b; Tanton and Edwards, 2013b) and in studies of other countries (e.g. Farooq et al., 2013; Müller and Axhausen, 2010). The most obvious data consideration is that the data must relate to the problem being investigated. There are also a number of high level issues regarding data selection for spatial microsimulation in general not just this case study. Table 7.1 summarises these. The key high level point is to ensure consistency between data sets as far as possible.

Table 7.1 High level data issues for spatial microsimulation

The categories in this checklist are after (Cassells et al., 2012) and (Williamson, 2012)

Issue	**Notes**
Sample scope	Surveys may exclude certain groups such as those living in hospitals or prisons, whereas the census includes these residents. If these groups have a major influence on the model, this inconsistency between data sets can introduce bias and error (Cassells et al., 2012). For representativeness, the sample population should capture the range of variation present in real population (Barthelemy and Toint, 2012; Birkin and Clarke, 2012).
Unit of analysis	Households or individuals are the most common units of analysis. The unit chosen has to be relevant to the problem being addressed (Cassells et al., 2012).
Attribute definition	Attributes of the same name may have different categories. As a simple example, age may be categorised in single years in a survey and in age groups in the census. Data processing is needed to make the data consistent (Cassells et al., 2012).
Temporal differences	A survey and a census may have been conducted in different years. If attributes of interest change a lot between years e.g when examining financial data, these differences can cause error (Cassells et al., 2012).
Account for deliberate errors introduced to census data.	To protect the confidentiality of respondents, national censuses introduce deliberate errors into small area data. In the UK it has been called SCAM: the Small Cell Adjustment Method. In Australia is has been called balancing (Cassells et al., 2012).
Appropriate constraint choice	The constraints must capture population variation (just as above the sample population table must). Constraints must be correlated to unconstrained attributes. Select constraints of interest in analysis. Trade off these first three requirements against computer processing time and storage (Williamson, 2012).

To discuss the data requirements of this specific case study, the chapter is organised as follows: Section 7.2 discuses and justifies the choice of constraints for stage 1 of the spatial microsimulation. They are dealt with first because constraints are the data central to the spatial microsimulation process (as explained in Sections 5.4.4.2. and 6.4.1).

Section 7.3 gives a brief overview of the data sets used in this case study. Section 7.4 firstly describes the processes used to generate constraint tables and a sample population table for stage 1 of the spatial microsimulation (see Figure 6.1 and 6.4 for details of the spatial microsimulation stages and how they fit into the overall modelling process). It also describes data processing of the attributes added to individuals in stage 2 of the spatial microsimulation. Section 7.5 discusses how the high level issues, which relate to spatial microsimulation in general listed in Table 7.1, are addressed with specific regard to this case study. Specific issues relating to individual data sets are also discussed.

7.2 Choosing constraints for stage 1 of the spatial microsimulation

Constraints are attributes common to both the sample population and the aggregate spatial data for each zone of interest (usually the census) (Ballas et al., 2005b; Tanton and Edwards, 2013b). The nature of a sample population table was explained in Section 5.4 and 6.4.1. Constraints can only be chosen after the sample population data set has been chosen. Ideally the sample population, used in stage 1 of the spatial microsimulation in this case study, would contain all of the following personal attributes which are required as inputs to part 2 of the modelling process (see Figure 6.4).

VO_{2max} (in ml/kg/min, a measure of fitness in terms of the body's ability to make use of oxygen for exercise, see Section 5.7.1 for further details)
Physical activity
Body Mass Index
Age
Gender
Weight
Bicycle availability
The need to escort children on the way to or from work

Some of the attributes required may be common to the sample population and the census constraint tables such as age and gender. The other attributes in the list are unconstrained attributes, so the sample population will have to contain attributes correlated to the unconstrained attributes, which are common to the sample population and the census (see for example Williamson 2012 and the discussion in Section 5.4.2).

The only dataset which measured all the key attributes for physical effort required to travel by walking and cycling; $VO2_{max}$, BMI and physical activity was the 2008 version of the Health Survey for England (HSE). In that year physical activity was the focus of the survey (Craig et al., 2009). However, the HSE, which was chosen as the data source for the sample population does not include all the personal attributes listed above. Bicycle availability and whether an individual needs to escort children has to be added in stage 2 of the spatial microsimulation (stage 2 was explained in Section 6.4.2).

Other data sets were considered for use as the sample population for stage 1 of the spatial microsimulation. There are a number of national surveys which are recommended as potential sample populations for UK based spatial microsimulation by Ballas et al., (2005b) including the New Earnings Survey, the Family Expenditure Survey (FES), General Household Survey (GHS), Labour Force Survey (LFS) and the British Household Panel Survey (BHPS) (which has been succeeded by the Understanding Society Database). These do not contain sufficient information about the personal physical attributes required by the modelling process.

Connected to the choice of sample population data set is the choice of whether to construct an individual or household level spatial microsimulation. In this case study an individual level population was built. It is a simpler approach than building a population of individuals within households. The fact that this is the first version of this type of indicator is a justification for taking a simpler approach. A second justification is that though a great deal of individual *travel behaviour* is influenced by the household (Barthelemy and Toint, 2012), the focus of this study is *capacity* not *behaviour.* That said it is acknowledged that some simplifying assumptions will have to be made. For example simplifying assumptions are made about whether an individual has to escort a child where a more detailed household model could give a more accurate picture.

The unconstrained attributes in the HSE which are used are:

$VO2_{max}$ (ml/kg body mass/min)
Physical activity
Body Mass Index
Weight

7.2.1 Criteria for choosing constraints once the sample population has been chosen

There are three criteria for choice of constraints (Voas and Williamson, 2001). The first two are correlation with unconstrained attributes and the interest in the constraint attributes for analysis. These are traded off against the third constraint; the need to limit the number of constraints so that computer processing time fits with the time scale of the work. Voas and Williamson, (2001) found that once the constraints with the strongest correlation had been included, there was very little gained by adding large numbers of extra constraints with weaker correlations. In the following sections, a justification is made for using the following constraints: Age, gender, economic activity, Limiting Long Term Illness(LLTI), education and NSSEC (National Statistics Socio-Economic Classification). This is done by referring to associations between these attributes and VO_{2max}, BMI and physical activity. Following that a justification is offered for rejecting other candidate constraints.

7.2.2 Justification of age and gender as constraints

In healthy adults who exercise regularly, VO_{2max} declines relatively little until the age of 40 (shown in Figure 7.1using data from McArdle, 2010). Sex and age were found to have the strongest associations with VO_{2max} (ml/kg body mass/min), BMI and exercise when the HSE data was examined (see Figures 7.1- 7.3 respectively). The HSE sample is not limited to just healthy active individuals, it includes sedentary unfit individuals as well, to be more representative of the general population. This explains why the decline in VO_{2max} in Figure 7.1 begins before age 40 and is steeper than for fit active people.

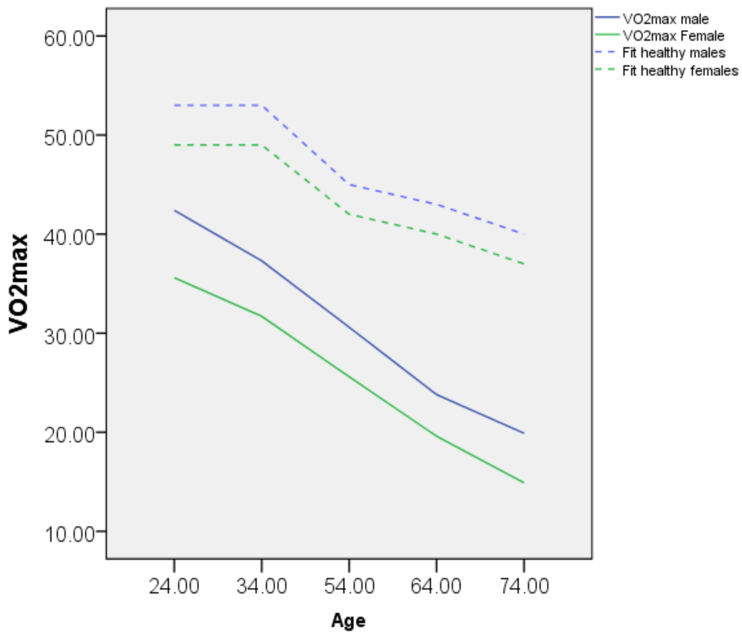


Figure 7.1 VO_{2max} (ml/kg body mass/min) versus age by sex taken from the sample population

Data for fit healthy individuals from McArdle, 2010 p169, data for sample of population from the Health Survey for England 2008 who completed a step test . Source: Health Survey for England 2008.

Mean BMI given gender can clearly be seen to rise with age in Figure 7.2 below. This further suggests age and gender as good candidates to be constraints.

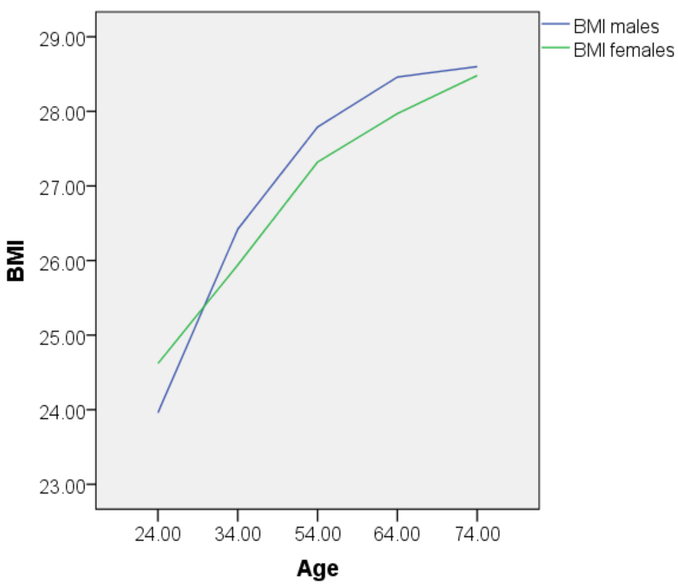


Figure 7.2 BMI versus age by sex taken from the sample population

Source: Health Survey for England 2008.

The HSE data aims to represent the population as a whole, including the large proportion who do not exercise regularly. The HSE data shows there is a marked difference in exercise between young males and females (see Figure 7.3), though due to a rapid decline in the level of physical activity in men with age, activity levels are similar in older men and women. The Sport England Active People Survey also found an association between physical activity and age and gender (IPSOS MORI, 2007). The clear variation in physical exercise with age and gender make them good candidates to be constraint variables.

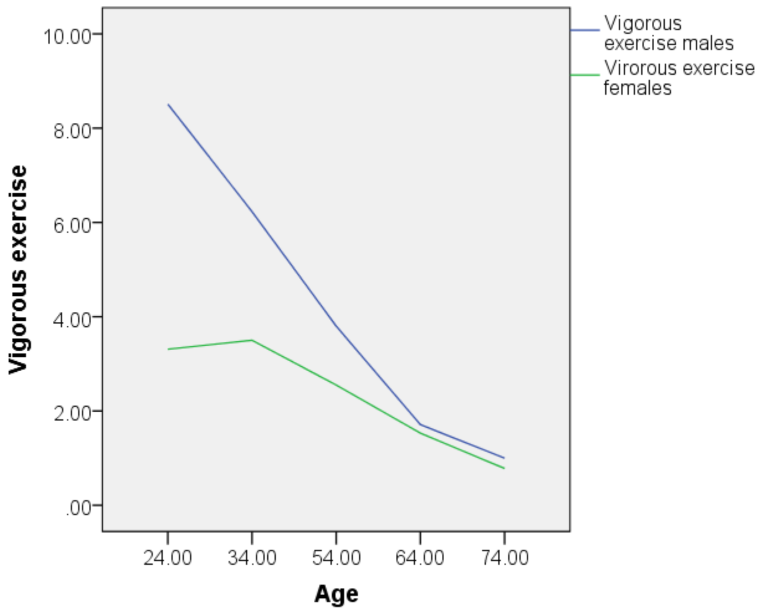


Figure 7.3 Vigorous exercise versus age by sex taken from the sample population.

Vigorous exercise is the number of episodes of at least 30 minutes over the past 4 weeks Source: Health Survey for England 2008.

7.2.3 Justification of economic activity as a constraint

Age and gender alone would not capture all the variation in VO_{2max} (ml/kg body mass/min), BMI and physical activity. There are socio-economic factors which influence these attributes. Economic activity is a candidate socio-economic constraint. Economic activity is an attribute of interest in its own right: Those who are working are the individuals to be considered in the indicator. The HSE data suggests that there may be differences in VO_{2max} depending upon economic activity as shown in Figure 7.4. Students have higher average VO_{2max}. Economically inactive people appear to have lower VO_{2max} than students, but not markedly different to employed and unemployed groups. Associations are also suggested between economic activity and BMI. Figure 7.5 suggests that on average, students have lower

BMI scores. Students also appear to engage in more vigorous physical activity than the other groups as shown in Figure 7.6.

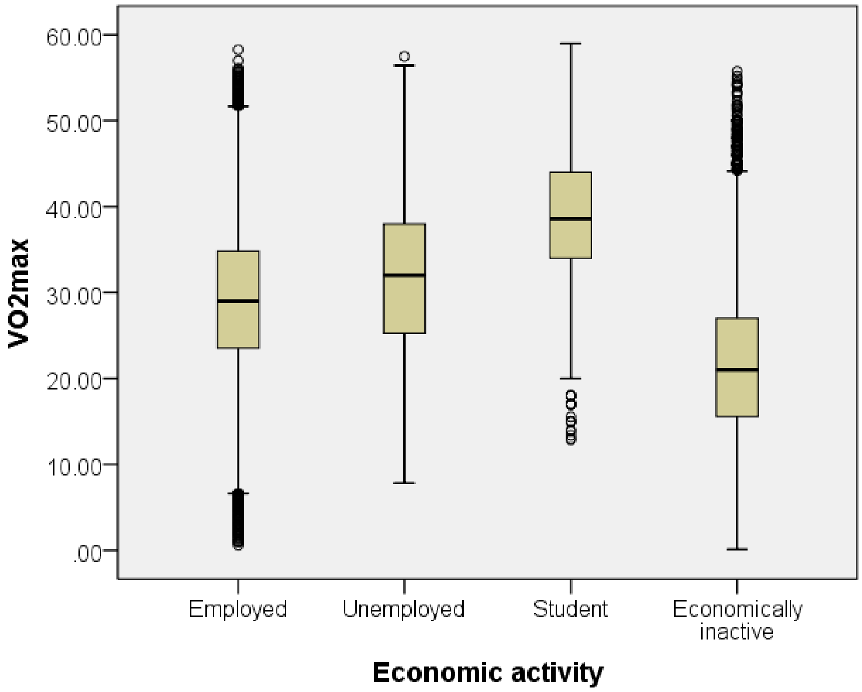


Figure 7.4 VO_{2max} (ml/kg body mass/min) by economic activity constraint

Students are associated with higher levels of fitness (VO_{2max}). Economically inactive individuals are associated with lower levels of fitness. Source: Health Survey for England 2008.

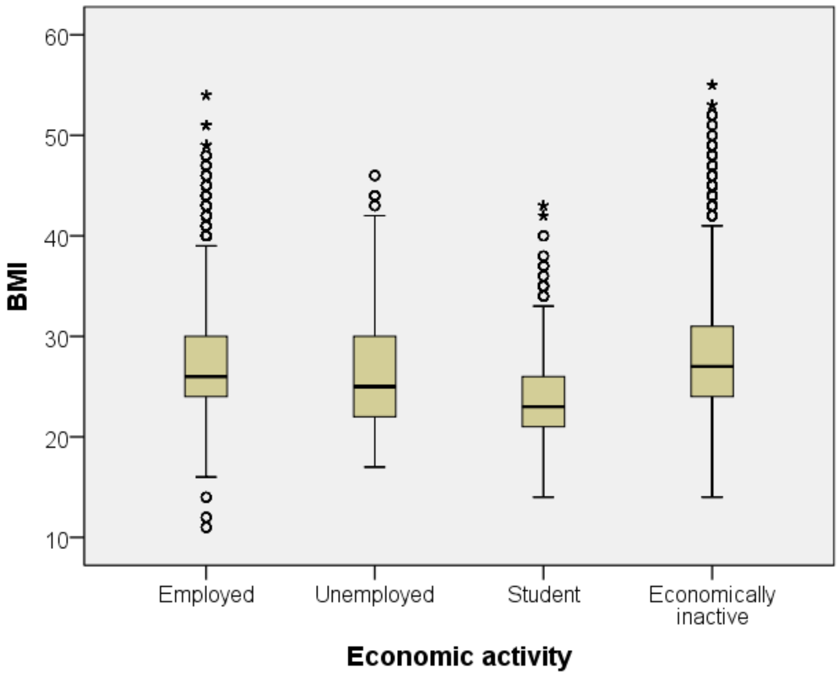


Figure 7.5 BMI by economic activity constraint

Students are associated with lower Body Mass Index (BMI). Source: Health Survey for England 2008.

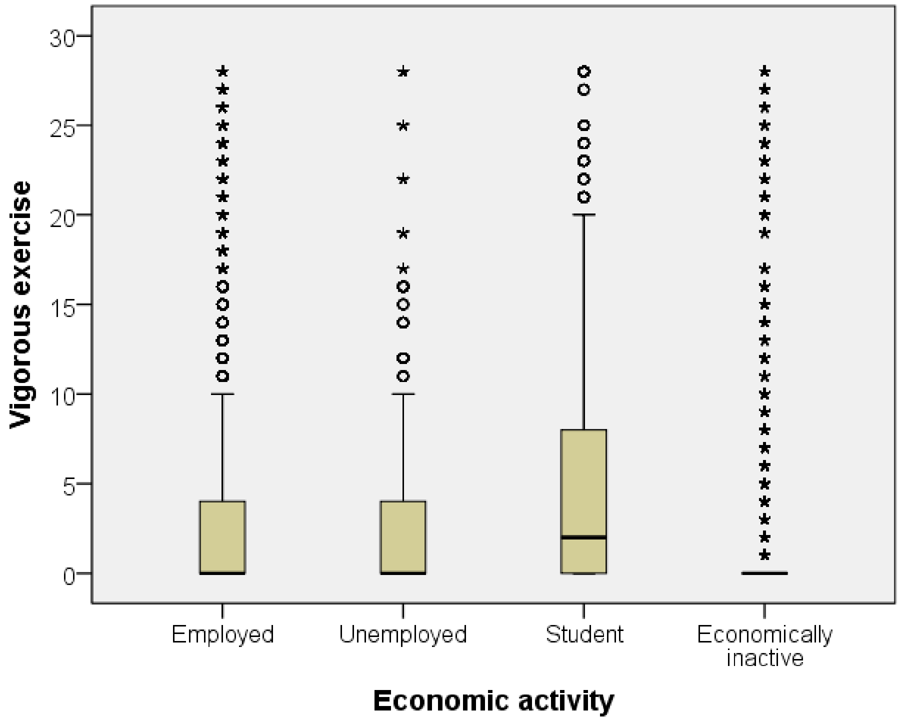


Figure 7.6 Vigorous activity by economic activity constraint

Consistent with Figures 7.4 & 7.5 students are also associated with higher levels of vigorous exercise. Source: Health Survey for England 2008.

7.2.4 Justification of Limiting Long Term Illness (LLTI) as a constraint

Limiting Long Term Illness is associated with higher levels of obesity, lower levels of physical activity and lower VO_{2max} in the HSE 2008 report (Craig et al., 2009). This can be seen in Figure 7.9. Obesity was also found to be associated with LLTI when the HSE data over several years was analysed by the National Obesity Observatory (NOO, 2010). Figure 7.8 shows that there is an association between BMI and LLTI. Figure 7.7 also shows LLTI having an effect, VO_{2max} is lower for those without a Limiting Long Term Illness.

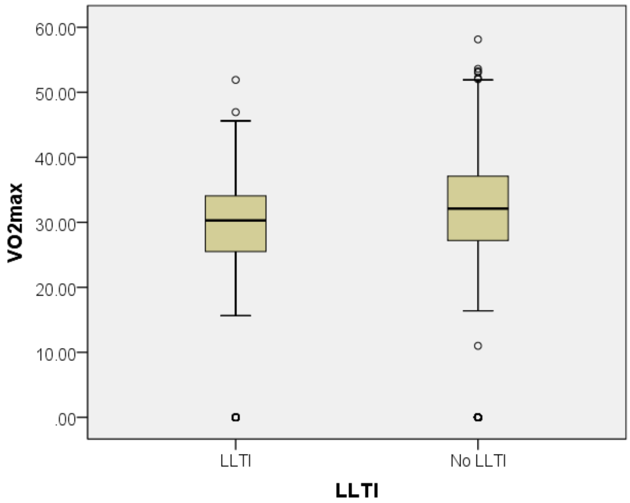


Figure 7.7 VO_{2max} (ml/kg/min) by LLTI

Source: Health Survey for England 2008

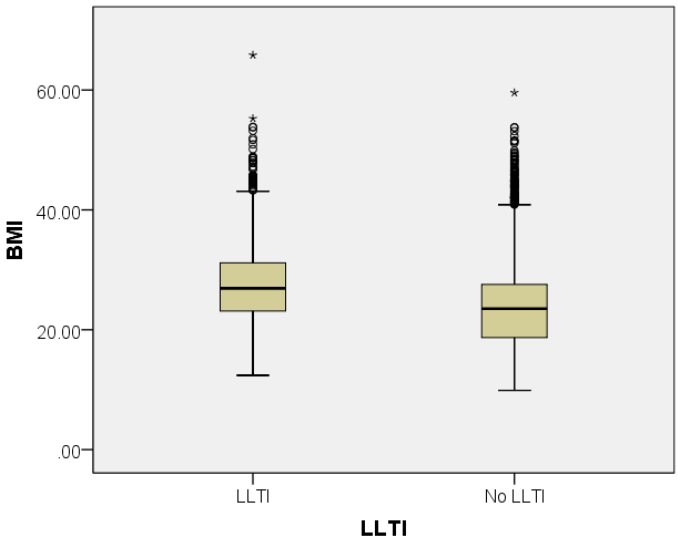


Figure 7.8 BMI by LLTI

Source: Health Survey for England 2008

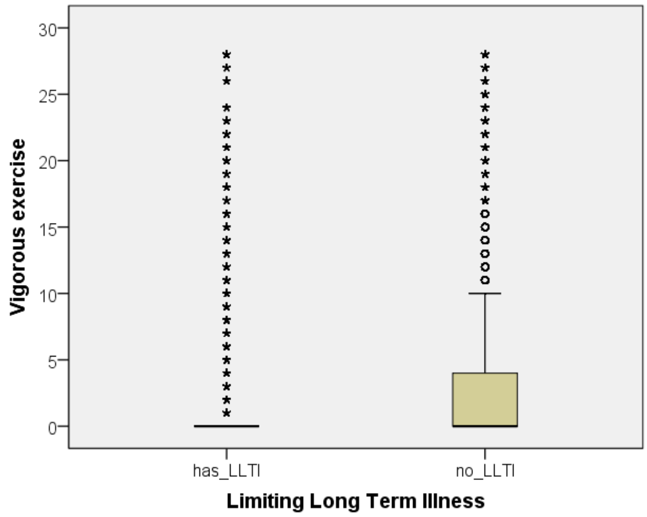


Figure 7.9 Vigorous exercise by LLTI

Source: Health Survey for England 2008

7.2.5 Justification of education as a constraint

The VO_{2max} inter quartile range (the shaded box) of those with no qualifications or 'other' qualifications are lower than those with higher levels of UK qualifications as shown in Figure 7.10. There did not appear to be a strong association between BMI and education in the 2008 HSE data.

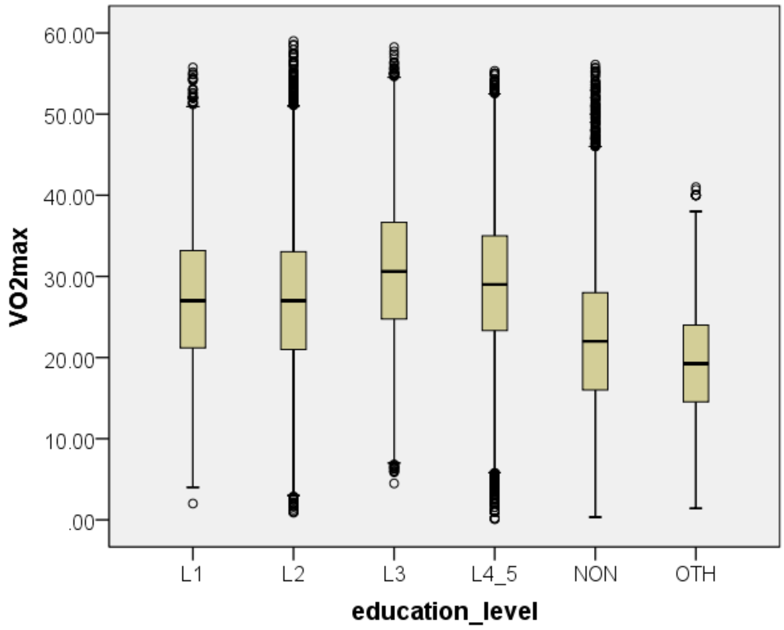


Figure 7.10 VO_{2max} (ml/kg/min) by education level

Having no educational qualifications or 'other including non-UK qualifications' is associated with lower fitness levels. Source: Health Survey for England 2008

IPSOS MORI, (2007) report an association with physical activity and level of educational attainment. The HSE 2008 data shown in Figure 7.11 suggests that higher levels of vigorous exercise are associated with those with higher UK qualifications.

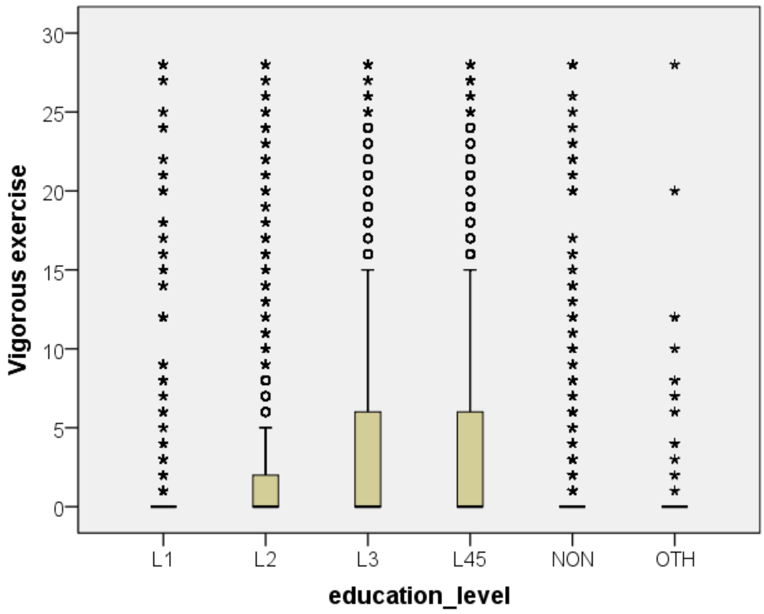


Figure 7.11 Vigorous activity by education level

Source: Health Survey for England 2008

7.2.6 Justification of National Statistics Socio-Economic Classification (NSSEC) as a constraint

From an analysis of several years of HSE data, it is suggested that NSSEC is associated with BMI (NOO, 2010). IPSOS MORI, (2007) report in the Sport England Active People Survey that NSSEC is the most strongly associated socio-economic variable with physical activity. More specifically those in NSSEC category 2 (lower managerial and professional) are the most likely to engage in physical activity and sport. The HSE data differs slightly from the Active People Survey in suggesting that those in the highest NSSEC category have even higher levels of physical activity than those in group 2 as shown in Figure 7.12. In general NSSEC is clearly associated with vigorous exercise, but associations with VO_{2max} and BMI were not obvious from plots.

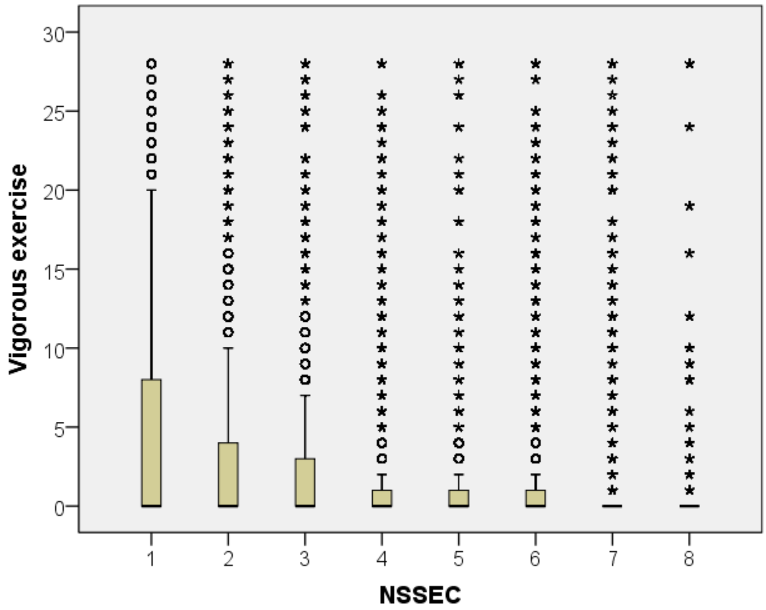


Figure 7.12 Vigorous activity by NSSEC

NSSEC class 1 is “Higher managerial and professional” whilst 8 is “Never worked and long term unemployed”. The higher social classes are associated with higher levels vigorous exercise. Source: Health Survey for England 2008

7.2.7 Justification for rejecting other candidate constraints

The Active People Survey suggested correlation between housing tenure and physical activity levels (IPSOS MORI, 2007) and studies have suggested a link between housing tenure and BMI (Macintyre et al., 1998). There are four reasons for excluding housing tenure. Firstly, several socioeconomic constraints have already been identified. To add another would greatly increase processing time. Secondly, housing tenure is associated with other socio-economic variables such as education and NSSEC which are included. Thirdly tenure is a household rather than individual level attribute and this model is individual rather than household based. Finally including too many constraints can reduce the fit of the model (Voas and Williamson, 2000).

Government Office Region was excluded as a constraint, though Craig et al., (2009) suggested it had a correlation with physical activity. The relationship did not appear prominent when looking at the HSE data. Moreover, had the region constraint been used it would have greatly reduced the number of individuals which could be drawn from the sample population. A sample population with too few individuals can lead to a model with a poor fit particularly when synthesising populations of very atypical zones (Cassells et al., 2012; Edwards and Clarke, 2012). The Index of Multiple Deprivation

(IMD) was another potential constraint. Deprivation is associated with obesity (NOO, 2010). The IMD was used in a spatial microsimulation of obesity by (Edwards and Clarke, 2012). The resolution of their analysis was slightly coarser; Lower layer Super Output Area (LSOA ~1500 people per zone) rather than Output Area (OA ~300 people per zone) – the resolution of interest for this case study. Deprivation was also considered for inclusion in the same way as Government Office Region, but for the same reason it would have reduced the effective size of the sample population. Adding either constraint would also have increased processing time and may not have improved the model.

Following the justification and examination of the data above the following constraints were chosen:

- Age
- Gender
- Economic Activity
- Limiting Long term Illness (LLTI)
- Education
- National Statistics Socio- Economic Classification (NSSEC).

7.3 Overview of datasets used

The data sets listed provide small area aggregate data and detailed attribute data about individuals.

- UK 2001 census: Small area aggregate data
- Health Survey for England (HSE) 2008 [micro-data]
- National travel survey 2010 [micro-data]
- National travel Survey (NTS) aggregate data. (2010)
- SRTM (Shuttle Radar Topography Mission) digital elevation data (2000)
- Children and Early Years Survey (2010)
- British Wind Energy Association (BWEA) / DECC wind speed data (1970’s &1980s).
- Bicycle characteristics from (Wilson, 2004)
- Bike availability by income (Anable, 2010)

7.3.1 UK Census 2001

The UK census is taken at 10 year intervals. The 2001 census was taken on April 29 2001[26]. Completed census forms represented 98% of the population. Additionally a census coverage survey was undertaken. The

[26] The indicator was constructed in 2013. 2001 census data had to be used because not all of the 2011 census data had been released in time to be used.

census coverage survey results were compared to the census, to assess the accuracy of the census. It interviewed a sample of households ensuring the most accurate possible answers to the census questions. These answers were compared to the census forms, identifying where inaccuracies or omissions occurred (Office for National Statistics, n.d.). Combining the census and coverage survey gave an appropriate basis for filling in missing data. This means that there is justification for assuming the census data gives complete coverage. The UK 2001 census has a number of outputs including aggregate data. The resolutions at which data are available are given in Figure 7.13 and Table 7.2. Not all data are available at all resolutions. Some data are provided as tabulations of single variables and others as part of cross tabulations.

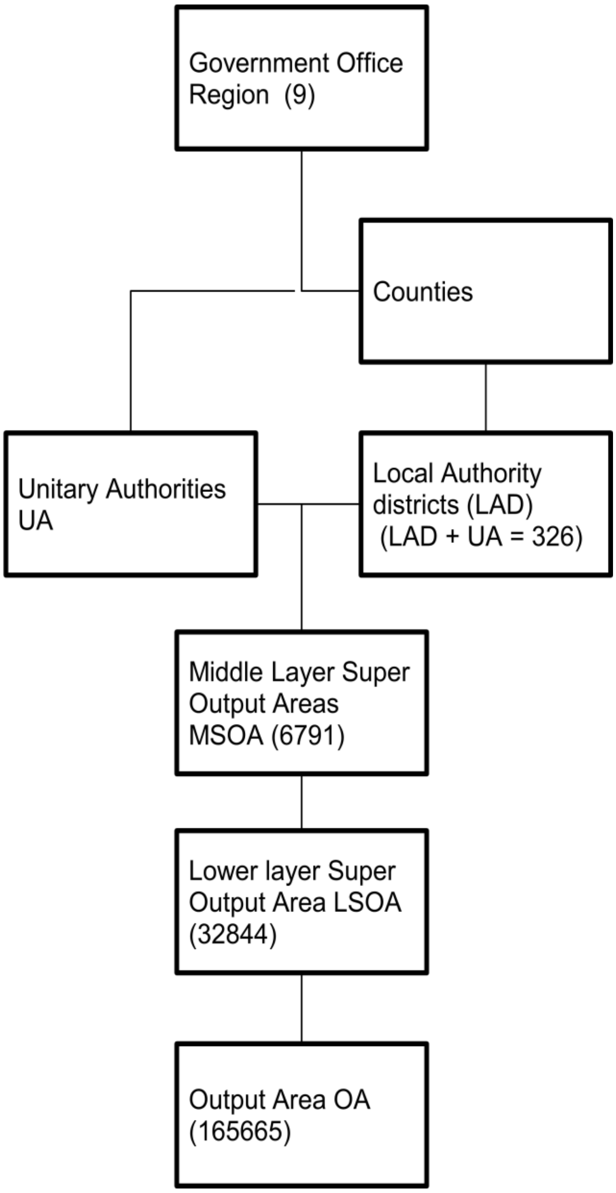


Figure 7.13 UK census Geographies 2001

(After Office for National Statistics, n.d.)

Table 7.2 Neighbourhood Statistics Geographies.

Source (Office for National Statistics, 2007). This table and Figure 7.2 above illustrate the resolution and hierarchy of spatial units used by the UK census. Indicator values are reported at OA level - the smallest aggregate unit.

Census geography: Neighbourhood statistics geographies	**Information**
Output Area (OA)	Mean population 309, typically populations are over 100 and under 625.
Lower Layer Super Output Area (LSOA)	Average population 1500. OAs nest into LSOAs. Typically 4 – 6 OAs per LSOA.
Middle Layer Super Output Area (MSOA)	Minimum population 5000, average population 7200. LSOAs nest within MSOAs. MSOAs nest within Local Authority Districts (LAD) / Unitary Authorities.

The UK census is widely used in spatial microsimulation studies (for a range of examples see Tanton and Edwards, 2013 and Section 5.4.1.1). Several data tables taken from the census were used to build constraint tables in stage 1 of the spatial microsimulation and also to allocate commute distances to individuals in stage 2 of the spatial microsimulation.

7.3.2 Health Survey for England (HSE) 2008

The Health Survey for England has been carried out annually since 1995 (Craig et al., 2009). Each year a set of core questions are asked plus supplementary questions with a particular focus. The 2008 edition focussed on physical activity and fitness (Craig et al., 2009). The sampling was stratified to include even representation across all 9 English Government Office Regions. 1,176 postcode sectors were selected, from a total of ~ 11,000, with 13-15 addresses randomly selected for interview from each of these. In total 16056 addresses were approached in the core sample. All adults and up to two children from each household were eligible to be included in the sample (Craig et al., 2009). The household response rate was 64%. 15,102 adults were interviewed. All participating households were offered a nurse visit. The nurse asked further questions and took measurements including weight and height. The nurse also carried out a step test on a sub-sample of the respondents which gave a measure of VO_{2max} (Craig et al., 2009). Two data sets are released; a household dataset with a smaller number of variables and a more detailed individual data set. The individual data set was used. The source of the data is: http://discover.ukdataservice.ac.uk/catalogue/?sn=6397&type=Data%20catalogue

The HSE micro-data was used to build the sample population used in stage 1 of the spatial microsimulation.

7.3.3 National Travel Survey (NTS) 2010

The National Travel Survey is carried out annually on behalf of the UK Department for Transport. The purpose of the survey is to provide information on personal travel patterns in the UK. Data is collected on the following: household, individual, vehicle, long distance journey, day, trip and stage using a combination of interview and seven day travel diary. Data is released as aggregate summaries and anonymised individual data. The sample size was 15,048 addresses in 2010 (DfT, 2010b). The NTS data was used in stage 2 of the spatial microsimulation to provide probabilities of bicycle availability and need to escort children during commuting. The data is available from: https://www.gov.uk/government/collections/national-travel-survey-statistics

7.3.4 Shuttle Radar Topography Mission (STRM) digital elevation data (2000)

A digital elevation data set was required to estimate road gradient. The Shuttle Radar Topography Mission (SRTM) dataset was used. The data was originally collected by NASA in the year 2000 with a horizontal resolution of 25 x 25m over the UK. Data is freely available at a 90m resolution (that is in a grid of 90m squares) and is regarded as the best freely available global digital elevation data set (Nikolakopoulos et al., 2006). This type of data set is usually referred to as a Digital Elevation Model or (DEM). The vertical resolution is reported for each continental landmass. Eurasia has a 90% absolute error of 6.6m. This means that a sample of the data was compared to known heights surveyed on the ground in a validation exercise and in 90% of cases the ground surveyed and SRTM heights were within plus or minus 6.6m of one another. The largest errors tend to be found where there are no roads; in very steep terrain such as Himalayan valleys or on large bodies of water (Jarvis et al., 2004). Where there are errors in digital elevation data, 'holes' caused by missing data and other erroneous values can be corrected by aggregation and spatial analysis procedures. UK academic institutions have access to a version of the SRTM data which can be downloaded as a .img file with a 75m horizontal resolution. This version has been re-sampled to match the British National Grid coordinate system. This dataset was used. The data are available from:

http://landmap.mimas.ac.uk/index.php/Datasets/SRTM/Characteristics-SRTM

It was chosen as an example of an internationally available data set available freely or at little cost, in an attempt to show that the model can be applied more widely than just the England case study area. In other countries, the freely available data could be re-sampled to a local co-ordinate system using a GIS package. Other proprietary data sets are available. In the UK other elevation data sets are available from the Ordnance Survey.

7.3.5 Children and early years survey (2010)

Data to estimate the probability of having to escort a child came from several sources including the Childcare and Early Years Survey. It contains estimates of the number of children aged under 5 who access child care (Smith et al., 2010). These estimates were extracted from tables in the report. Multiple attributes are derived from some of the data sets above. This dataset and the three below provide input only to single attributes. They require less introduction as their source information and the attribute they contain is easily explained.

7.3.6 British Wind Energy Association (BWEA) wind speed data.

This data is released jointly by BWEA and DECC (the UK Department for Energy and Climate Change). The wind data set gives mean annual wind speeds at 10m above ground level. Results are based on wind monitoring data, which is then interpolated and converted to a 1km x 1km raster grid. The data is available from:
http://webarchive.nationalarchives.gov.uk/20121217150421/http://decc.gov.uk/en/content/cms/meeting_energy/wind/onshore/deploy_data/windsp_databas/windsp_databas.aspx

7.3.7 Bicycle characteristics

Values for 'typical' utility bike characteristics were required. The simplifying assumption is made that all individuals with access to a bicycle have a utility bike. The values used are shown in Table 6.1. They are taken from Wilson (2004 p139).

7.3.8 Bike availability by income

An analysis of bike availability by household income data was presented in Anable, (2010) using the Scottish Smarter Choices Smarter Places (SCSP) programme based on a survey of ~12000 individuals. The data showed a clear association between bike availability and income. This data along with NTS data was used to derive a rough proxy for bike availability by individual National Statistics Socio-Economic Classification (NSSEC). It was then cross-tabulated with bike availability by age and gender.

7.4 Data set processing

Each data set required processing before it could be used as an input to the modelling process. Firstly, processing of the datasets used in the first stage of spatial microsimulation are described in 7.4.1 and 7.4.2, followed by comment on the efforts to ensure consistency between datasets in Section 7.4.3. After this the processing of the other data sets are described.

Following the choice of sample population and constraints discussed in Section 7.2, constraint tables were chosen from the 2001 census tables which were available at Output Area Resolution. The processing of the tables chosen is described below. The census tables chosen as constraint tables are:

Sex and age by economic activity CS028
NSSEC (National Statistics Socio-Economic Classification) by sex KS14 b/c
Limiting Long Term Illness CS021
Highest educational qualification KS013

7.4.1 Construction of constraint tables

The downloaded census data tables had to be processed before they could be used: The attributes in the constraint tables required categories consistent with the sample population. The constraint tables themselves also had to be consistent in terms of each zone having the same total population in every constraint table (considerations listed in Table 7.1).

Table 7.3 summarises the data sources used in the spatial microsimulation and how they relate to the variables described in the notation in Chapter 6.

Table 7.3. Summary of data sources used in part 1 of the modelling process: spatial microsimulation and their relationship to the model notation in Chapter 6

Attributes which are used as constraints have two data sources; for the aggregate constraint table and for the micro-data sample population. In the information about variable column, Notation is a reference to the equation in Chapter 6 where this attribute is used first.

Variable name	**Information about variable:**	**Source data set**	**attribute(s) used**
Employed population of zone j	*Notation is j* [6.2]	UK census 2001 : table CS028 Sex and Age by Economic Activity:	All People Aged 16 to 74
Employed individual	Sample population links to constraint in row above	HSE[27] Individual data table	Economic activity taken from variable “Econ_act”
NSSEC[28]	Constraint[29]	UK census 2001 tables KS014 b and c, NSSEC by sex	NSSEC by sex 10 male and 10 female categories
NSSEC	Sample population links to constraint in row above	HSE Individual data table	Derived from HSE attributes NSSEC, sex and student status
Age	Constraint	UK census 2001 table CS028	Age groups between 16 and 74
Age	Sample population links	HSE Individual data table	HSE attribute “Age at last birthday”

[27] Health Survey for England

[28] NSSEC: National Statistics Socio-Economic Classification.

[29] Choice of constraints was discussed in Section 7.2, the workings of constraints in Section 6.4 and the processing of constraints in Section 7.4.1 below for census constraint tables and 7.4.2 for the HSE sample population.

	to constraint in row above		
Sex	Constraint	UK census 2001 table CS028	
Sex	Sample population links to constraint in row above	HSE Individual data table	
LLTI[30]	Constraint	UK Census 2001 table CS021	Presence or absence of LLTI
LLTI	Sample population links to constraint in row above	HSE Individual data table	HSE Attribute "Limitill"
Highest educational qualification	Constraint	UK Census 2001 table CS021KS013	Education
Highest educational qualification	Sample population links to constraint in row above	HSE Individual data table	HSE Attribute "Topqual3"
$V0_{2max}$ (ml/kg/min)	*Notation is* O_i [6.7]	HSE Individual data table	HSE Attribute "VO_{2max} best avail" and modelled estimates
Height		HSE Individual data table	HSE Attribute "Height"
Weight of bike and rider.	*Notation is m* [6.10]	HSE Individual data table	HSE Attribute "weight" for rider weight
Body mass index (BMI)	*Notation is* BMI [6.8]	HSE Individual data table	HSE Attribute "BMIval"
Minutes of	*Notation is q*	HSE Individual	HSE Attribute

[30] LLTI: Limiting Long Term Illness

vigorous activity per week.	[6.8]	data table	"vig30sp"
Commute distance	*Notation is* X_{ij} *[6.3]*	UK census 2001 table CAS120 at Output Area level	Commute distance by age group and sex
Whether escort trips have to be made	*Affects* t_{ij} *in equation* [6.6]	NTS table 0611 Escort trips by age and gender 2010 HSE Individual data table Childcare and early years survey of parents 2009	Average number of escort trips trips by age and gender attributes Age, gender Percentage of children under 5 accessing child care / pre-school
Bike availability	*Notation is* S_{ij}^{bike} [6.4]	NTS microdata 2010 tables, individual, household. HSE Individual data table Anabele2010	Variables bike availability, age group and gender Variables "age", "sex", "NSSEC8" Bike availability by income.

7.4.1.1 Sex by age by economic activity based on census table CS028

Table 7.4 shows that the three constraints, sex, age and economic activity were constrained jointly using a cross-tabulated constraint table. The rationale is that cross-tabulated constraints are more accurate in terms of a better representation of the actual population. However, they are more complicated to set up than univariate tables.

Table 7.4 Constraint table sex by age by economic activity based on CS028.

CS028 has 8 age groups. Groups 16-17, 17-19 and 20-24 were amalgamated into one group. Economic activity grouped together all students into one category, all economically inactive individuals were placed in one category employed and self employed people were grouped as employed .

Sex	Male, female
Age	16-24, 25-34, 35-54, 55-64, 56-74
Economic activity	Employed, Unemployed, Student, Economically inactive

UK census table CS028 was processed to produce a constraint table consistent with both the sample population table and the other constraint tables. Age groups were altered to match the sample population. To maintain confidentiality, the census introduces deliberate errors in cell counts (Rees et al., 2002; Stillwell and Duke-Williams, 2003). It results in cell row and column totals not matching the total population. This results in different constraint tables having inconsistent numbers of individuals and creates errors in the distribution of attributes. Addressing this issue is one of the high level considerations highlighted in Figure 7.1. One method, used by Barthelemy and Toint, (2012), to try to address this issue is to convert all cells to a proportion of the total population. The individual cell values taken from table CS028 were expressed as a proportion of the total population. These proportions were not integers. The cells have to be integers to represent whole people. A relatively simple Excel VBA procedure was written, to ensure the cells firstly contained integer counts and secondly that the sum of the cells matched the population total for each Output Area. The procedure is described in Figure 7.14. However as it was quite simplistic it may not be completely error free – because the allocation of individuals left over from the rounding process have to be allocated arbitrarily.

Step 1	Calculate cell value based on frequencies *(Raw cell value / raw row total) * reference population total*
Step 2	Intergerise the decimal value from previous step *Round the value up or down*
Step 3	Account for rounding losses *If rounded value ≠ reference population total* *If reference population total < integerised row total* *then subtract 1 from a random cell in the row* *If reference population total > integerised row total* *then add 1 to a random cell in the row.*
Step 4	Repeat until rounded value = reference population total

Figure 7.14 Procedure for integer lossless conversion of cell values to match the population total for each output area.

7.4.1.2 Limiting Long Term Illness (LLTI) based on census table CS021.

CS021 contains economic status by gender by LLTI. The constraint table used only 2 categories; OA population with and without LLTI. The lossless rounding procedure in Figure 7.13 was used. Due to there already being cross tabulated constraints in use, this constraint was constructed as a univariate constraint. This was firstly to avoid large increases in processing time, secondly as economic activity and gender were already jointly constrained in the table above.

7.4.1.3 NSSEC by sex based on census tables KS014 (b and c).

KS014 b and c contain NSSEC by age, for males (b) and females (c). NSSEC by gender was used in the constraint, age was not used in this constraint. KS014 has 10 categories. The lossless rounding procedure in Figure 7.13 was used.

7.4.1.4 Highest educational qualification based on census table KS013

Table 7.5 shows the 8 categories in census table KS013. The final two categories double count individuals already counted in the other categories. Only the first six categories were used.

Table 7.5 Categories in the highest educational qualification constraint

Those shaded are recoded so constraint and sample population are consistent

Ks013 categories
None
Level 1
Level 2 (5 GCSE equivalent at A*-C)
Level 3
Level 4/5 (HND or above)
Other level unknown
Full Time students and school children age16-17
Full Time students age 18-74

7.4.1.5 CAS 120 sex and age by distance travelled to work

In addition to generating constraint tables used in stage 1 of the spatial microsimulation, the census data was also used in stage 2 (see Figures 6.1 and 6.4 for a recap of the stages in the modelling process). Census table CAS120 contains sex and age by distance travelled to work. table CAS120 was used to generate a cumulative frequency distribution table for each subgroup of the population (5 male groups and 5 female). The tables (see Table 7.6) were used in the modelling process to assign commute distance probabilistically to the individuals which had been generated in stage 1 of the spatial microsimulation. As explained in Section 6.4.2, commute distance has to be allocated in stage 2, after an individual is assigned to a location, because commute distance is geographically dependent.

Table 7.6 Layout of a commute distance cumulative distribution table based on CAS120.

Each sex by age sub-group has a table of this format The category 'Other' includes no fixed place of work and working outside the UK. The distances given are Euclidean distances between origin post-code centroid and work location postcode centroid.

	Commute distance in km								
Zone	home	0-2	2-5	5-10	10-20	20-40	40-60	>60	Other
AO1	0	0.1	0.2	0.3	0.7	0.7	0.9	1	1

Synthetic Individuals in the ‘Other’ category with no fixed place of work included trades people and sales representatives who work ‘on the road’. The simplifying assumption was made that all people in the ‘Other’ category would have considerable daily travel distances; more than it would be reasonable to walk or cycle, so they were given an arbitrarily high value of a 500km commute. The counts were split into sub-groups by age and gender. The counts for each sub-group in each Output Area were converted into a cumulative frequency distribution. The distributions allowed the probabilistic assignment of commute distance bins to individuals. Once assigned a bin, a simplifying assumption was made. The distribution of individual travel distances within each bin was assumed to be uniformly distributed. To make the commute data consistent with the estimations of maximum distance that individuals could travel, a circuity factor was applied as shown in Chapter 6 equation [6.3]. To account for circuity (ratio of network distance to Euclidean distance), the Euclidean commute distance X_{ij} is multiplied by a circuity factor z. Newell, (1980) suggested 1.2 but more recent estimates suggest it may be higher. Ballou et al., (2002) found English inter urban routes had a circuity of 1.4. More recently Levinson and El-Geneidy, (2009) have carried out analysis of circuity in US cities though it was felt better to base the assumption of circuity on studies of the UK.

7.4.2 Health Survey for England (HSE) data processing

The raw HSE micro-data was processed into a sample population. The sample population contained constraint attributes, which matched constraint tables, as well as unconstrained attributes needed to calculate the indicator as discussed in Section 7.2 above. Individuals in the HSE data set were processed in three sub-groups, then added to the sample population used in stage 1 of the spatial microsimulation.

7.4.2.1 Group 1

In the HSE, 1754 individuals completed a step test from which VO_{2max} is estimated using a calibrated protocol. (Brage et al., 2007; Craig et al., 2009). These individuals had the attributes: height, weight, VO_{2max}, BMI and level of vigorous exercise plus the constraint variables Age, gender, education, limiting illness and NSSEC (National Statistics Socio-Economic Classification). Brage et al., (2007) suggests step tests typically have an error of +3.9 to – 5.8. The listed VO_{2max} value for each individual was taken and a VO_{2max} assigned probabilistically about the reported variation. Pedal Power was calculated based on the VO_{2max} value and the other attributes. Pedal Power, as explained in Section 5.7, is also assigned with a probabilistic element to account for the variation of Lactate Threshold, and the effect of exercise on fitness between individuals. To capture more of the variation between individuals, which is known to exist in the population at large, Monte-Carlo sampling was used. Ten draws of each individual were made. The Monte-Carlo generated individuals were added to the sample population.

7.4.2.2 Group 2

The HSE data contains 113 individuals unable to complete the step test and categorised as “very unfit”. These were given a VO_{2max} value of 13 by Craig et al., (2009). Pedal Power was assigned and multiple draws made to add to the sample population in the same way as for group 1.

7.4.2.3 Group 3

9246 individuals had all the attributes as above except VO_{2max}. A VO_{2max} value was estimated using the regression model in Table 7.7. The 95% confidence interval reported in Wier et al’s model is +-4.9 ml/kg/min.

Table 7.7 Regression estimate of VO_{2max} Source (Wier et al., 2006 p558)

Sample size;n male = 2417, n female = 384. Measured range of VO_{2max} = 15-66, BMI range 16-48.

Attribute	Beta
constant	57.402
age	-0.372
gender (M=1, F=0)	8.596
PASS (Physical Activity)	1.396
BMI	-0.683
Error ml/kg/min (95%ci)	4.9

Before the regression model could be used, the vig30sport variable in the HSE (Number of occasions spending 30+minutes doing sport or vigorous activity in the past 4 weeks) was approximated to the Physical Activity Status Scale (PASS) variable (see Table 7.8). PASS is an activity and exercise scale developed by NASA, (Wier et al., 2006).

Table 7.8 Conversion of HSE variable 'Vig30sp' to PASS values used in the modelling process.

(* assigned with equal probability)

Vig30sp value	PASS value
0	1,2,3 *
1-4	4
5-8	5
9-16	6
17-24	7
>24	8,9,10 *

To account for the error in the model, the initial VO_{2max} value for each individual estimated using the regression model was used to assign VO_{2max} probabilistically based on the reported variation. Monte-Carlo sampling was used to add 10 versions of each generated individual to the sample population.

7.4.3 Processing to ensure consistency between sample population and constraint tables

The construction of the constraint tables is described in Section 7.4.1 above. Some of the attributes in the HSE are recorded with different categories than in the constraint tables. Some categories in the HSE were processed by reclassification to make them consistent with the constraint tables. The paragraphs below describe the reclassifying of the HSE data which gave sample population attribute categories consistent with the constraint tables described in Section 7.3.2. Before processing, records with null values in any category used as a constraint or in the model were removed.

7.4.3.1 Economic activity by age and sex

Age of individuals in years appears in the HSE. Individuals were given an age group matching the age groups used in the constraint tables. Sex did not need processing. Economic activity was taken from the "econ_act" variable. It did not include students, unlike the constraint table. The HSE variable 'FT student' was used to reclassify any full time students as students. The categories for economic activity were; employed, unemployed, student and economically inactive to make it consistent with the constraint table derived from CS028.

7.4.3.2 Education

The coding of categories in the HSE did not match the census coding. The HSE variable topqual3 was re-coded as shown in the Table 7.9.

Table 7.9 Recoding of HSE variable Topqual3 to match the census Table KS013

Census table Ks013 education categorised used in constraint table	**HSE ‘topqual3’ variable**
None	7
1	5
2	4
3	3
4/5	1 and 2
Other level unknown	6

7.4.3.3 LLTI (Limiting Long Term Illness)

The categories in the HSE “limitill” variable matched the census data but with different codes. The variable was reclassified to match.

7.4.3.4 NSSEC by sex

In the census tables KS014b and c, there are 10 NSSEC categories by sex. Generally, once constraints are chosen, amalgamation of categories should only be done to ensure constraint and sample population tables were consistent. Excessive amalgamation of attribute categories can reduce the fidelity or representativeness of the synthetic population (Müller and Axhausen, 2010; Voas and Williamson, 2001). The long version of the NSSEC classification was used to produce a consistent classification in the HSE based sample population as shown in Table 7.10.

Table 7.10 The long version of the NSSEC classification was used to make 10 categories consistent with the constraint table.

NSSEC group from KS014	NSSEC groupings in constraint table	NSSEC groups from HSE variable 'stnnsec' (NSSEC long version)
Large employers and higher managerial occupations Higher professional occupations	1	1 through 3.4
Lower managerial and professional occupations	2	4 through 6
Intermediate occupations	3	7 through 7.4
Small employers and own account workers	4	8 through 9.2
Lower supervisory and technical occupations	5	10 through 11.2
Semi-routine occupations	6	12 through 12.7
Routine occupations	7	13 through 13.5
Never worked Long-term unemployed	8	14 through 14.2
Full-time students	9	15 through 15.2
cannot be classified	10	16 through 17

Ideally, there should be individuals in the sample population which fall into every category. The constraint table category "cannot be classified" does not appear in any individual in the sample population with a complete record, but it does appear in the census constraint tables. The Simulated Annealing algorithm cannot find a perfect solution in these zones. It increases the error measures discussed in the validation tests in Section 5.4.3 and Chapter 8 as well as the processing time. Reducing the number of attribute categories can reduce this problem as stated above and give much lower error values, but, amalgamating categories can also cause loss of information and representativeness. Amalgamation of categories cannot cause an increase in information, so reductions in error arising from amalgamating categories should it seems be taken ‘with a pinch of salt’. Because of this, it is important to present the results without “hiding errors” by amalgamating NSSEC categories. However in Chapter 8, during discussion of model validation, comparisons are made between models with all the NSSEC categories and those with amalgamated categories.

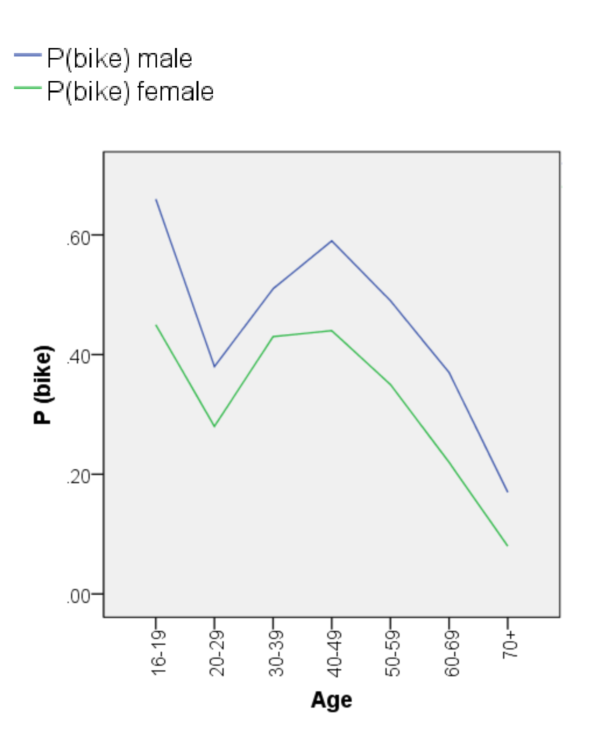
7.4.4 Processing of NTS data

7.4.4.1 Bicycle availability

The NTS micro-data 2010 individual and household tables were imported to a database. A query was used to collect the probability of having a bicycle available for use given age and gender. This is shown in Table 7.11.

Table 7.11 Probability of bike availability given age and gender using NTS 2010 individual data

P(bike available)	Gender	Age group
0.66	M	16-19
0.45	F	16-19
0.38	M	20-29
0.28	F	20-29
0.51	M	30-39
0.43	F	30-39
0.59	M	40-49
0.44	F	40-49
0.49	M	50-59
0.35	F	50-59
0.37	M	60-69
0.22	F	60-69
0.17	M	70+
0.08	F	70+



The probability of a person having access to a bike is, like most material goods, at least in part dependent upon socio-economic status. Anable, (2010) using data from the Scottish Smarter Choices Survey, found household income related to bike ownership. Household income is also strongly related to NSSEC – a constraint attribute (Voas and Williamson 2000). Though not ideal, a simplifying assumption was made that bike availability declines from NSSEC 1 through 8 (shown in Table 7.12). There is a degree of approximation in this approach, which has to be acknowledged as a limitation, but it follows the evidence that bike availability increases with wealth.

Table 7.12 The NSSEC component of bike availability (approximated).

NSSEC	% bike availability
1	75
2	55
3	55
4	25
5	25
6	25
7	25
8	25

The NSSEC and age/gender tabulations were used to form the row and column marginals of a cross tabulation. Iterative Proportional Fitting (IPF) was used to estimate the cell probabilities of the cross tabulation; bike availability given sex and age by NSSEC.

7.4.4.2 Escort trips data

As explained in Chapter 6, it is assumed that some people will need to escort children to school. It is assumed that this places a constraint on their time budget for commuting. People with children are identified in the HSE micro-data. These people had to be given a probability of needing to escort children to school, nursery or child-care. Data to estimate the probability of having to escort a child came from several sources. The child population by year was collected from the ONS (Office for National Statistics) mid-year population estimates (Office for National Statistics, 2009). The Childcare and Early Years Survey (Smith et al., 2010) contains estimates of the number of children aged under 5 accessing child care. Where parents are in employment, it is not known whether their child is cared for by a partner, a relative or if they use some form of nursery, pre-school or child minder. A simplifying assumption is made. All children under 5 of employed individuals need to attend child care the day following a shock. Table NTS0616, summarised whether children (aged 7-13) are accompanied to school by an adult. There was no data on the proportion of children aged 13-16 escorted to school by parents. Anecdotal evidence suggests the proportion is low. For that reason, the simplifying assumption was made that 13-16 year olds were not escorted to school. The data sets mentioned in this paragraph contribute to Table 7.13.

Table 7.13 Proportion of children under 16 escorted to school / pre-school or child care.

The percentage of workers' children escorted to education is taken from NTS Table 0616 2010 the other data is taken from the children and early years survey (Smith et al., 2010).

Age	**children by age**	**% of worker's children escorted to education**	**estimated number of escorted children**
0	672.1	100	672.1
1	661.5	100	661.5
2	667.8	100	667.8
3	645.6	100	645.6
4	633.6	100	633.6
5	608.2	100	608.2
6	598.1	100	598.1
7	579.7	84	486.948
8	567.7	84	476.868
9	580.6	84	487.704
10	596.1	84	500.724
11	614.2	30	184.26
12	622	30	186.6
13	639.5	30	191.85
14	637.4	0	0
15	636.7	0	0
total	*9960.8*		*7001.854*
percentage of all children under 16 escorted			**70%**

To summarise; for all adults with one or more children under 16:

$$P(individual\ i\ has\ a\ child\ under\ 16\ which\ is\ escorted\ to\ school) = 0.71$$

[7.1]

The proportion of escort education trips by males and females is estimated as follows: NTS Table NTS0611 includes the average number of education escort trips (trip rates) by age, gender and purpose. 59% of education escort trips were made by women and 41% by men. A simplifying assumption used here is that escort education trips are made by parents.

$$P(individual\ i\ escorts\ them) = \begin{cases} if\ Male & 0.41 \\ if\ Female & 0.59 \end{cases}$$

[7.2]

7.4.5 Gradient and slope profile processing

The SRTM (Shuttle Radar Topography Mission) dataset was used. This gave a grid where each 75m square cell has been given a height value. This data is then linked to a roads data set; the Ordnance Survey Meridian2[31] data set. The 2012 release in Shapefile (.shp) format, records entities as poly-line features for every link of road, and track in the UK. Each link terminates at a junction with another link. Subsets of these data sets were extracted to cover England. The “Add surface information” ARCGIS tool[32] was used to calculate gradient attributes for each route link. The mean gradient of network segments within 5km x 5km cells was then calculated. Following this, the Output Area centroids were added to the map as a point layer. Using the extract to points tool[33] the mean link gradient value of the 5km x 5km cell was added to each Output Area as shown in Figure 7.13. This gradient value was used in the maximum distance calculation for residents of each Output Area.

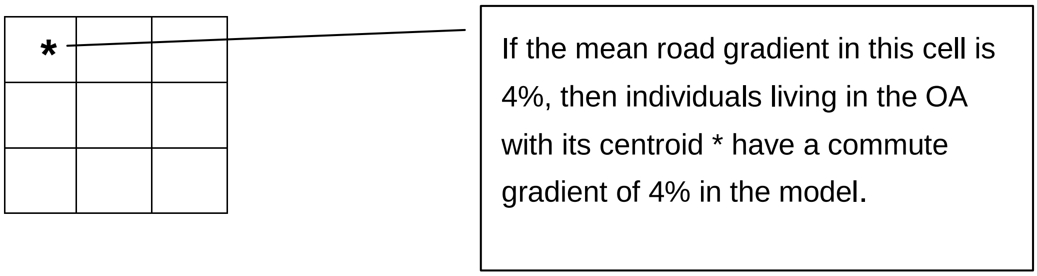


Figure 7.15 Allocating gradient to Output Areas.

The grid has 5km x 5km cells. The cell value is the mean gradient of all road / track links within it.

The slope profile is the proportion of a route that is up, down and flat. The proportion of up, down and flat were estimated for different 5km cells. A cell

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[31] Accessed via www.digimap.ac.uk.

[32] ARCGIS tool help http://resources.arcgis.com/en/help/main/10.1/index.html#//00q900000016000000

[33] Instructions on using these tools is available at http://webhelp.esri.com/arcgisdesktop/9.3/index.cfm?TopicName=welcome

with an average gradient of greater than 4% was selected. The proportion of segments in that cell with a gradient of less than 0.5% was calculated[34]. This gave an indication of what proportion of segments in that cell would be perceived by a cyclist as flat. The process was repeated for cells with differing average gradients. The cells were in Yorkshire and Humber region (Firstly because the region has a range of landscape types and secondly because of the author's familiarity with the region). Table 7.14 shows the results. The proportion of near flat segments decreases as average gradient increases. This analysis suggests that the most appropriate allocation of slope profile is to assume that a person's commute does include uphill, flat and downhill segments with a decreasing proportion of the route being flat as average gradient increases.

Table 7.14 Proportion of near flat route length in cells with different mean road gradient.

Area of sample	Mean slope	Proportion of network in sample area with slope < 0.5%[35]	Proportion of network in sample area with slope < 1%[36]
Vale of York	< 1%	25%	33%
Doncaster urban area	1- 2%	17%	46%
Harrogate urban area	2 -3%	7%	18%
North West Leeds	3-4%	5%	13%
Keighley	4-6%	5%	12%

7.4.6 Wind speed processing

The wind data set gives mean annual wind speeds at 10m above ground level. The friction of the ground affects the wind speed. The closer to the ground, the lower the mean wind speed. The rougher the ground, the more the wind is slowed. The processes at work are explained in detail in

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34 . A utility bike on a slope of less than 0.5% grade would not accelerate down the hill with a rider weighting up to 95kg.

35 The force due to rolling resistance of a person on a utility bike with 95kg total mass is greater than the force of gravity on gradients of less than 0.5%

36 On a mountain bike the force due to rolling resistance with 95kg total mass is greater than the force of gravity on gradients of less than 1%

McIlveen, (2010). To estimate the wind at 1.2m above the ground, the logarithmic wind profile is calculated: $h_{1.2}$ is the wind speed at 1.2m above ground and is used in Chapter 6 equation [6.12]. V_{10} is the known reference wind speed at 10m in this case. z is the 'roughness length', a parameter set depending upon the ground cover. The parameter chosen is 0.4. This includes areas classed as towns or villages[37].

$$h_{1.2} = V_{10} \frac{\ln\left(\frac{1.2}{z}\right)}{\ln\left(\frac{10}{z}\right)}$$

[7.3]

7.4.7 Rolling resistance

The simplifying assumption was made that all bikes had utility bike tyres with a rolling resistance of 0.008. This value is taken from (Wilson, 2004) and is consistent with the value assumed by Parkin,(2008).

7.5 Issues arising from datasets used

7.5.1 Summary of simplifying assumptions arising from data availability

A number of simplifying assumptions have had to be made as a result of the data available. It is assumed that:

- The census represents the whole population
- People with non-fixed work places have a daily travel distance greater than their maximum commute distance
- Within bin commute distances are distributed uniformly
- All children under 5 of employed individuals need to attend child care the day following a shock
- 13-16 year olds are not escorted to school
- Escort trips to education and child care are made by parents
- The slope profile of a commute journey includes uphill downhill and flat segments.
- Cyclists ride in a head wind on one leg of their commute journey

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[37] A full table is available at :

http://wind-data.ch/tools/profile.php?h=10&v=4&z0=3&abfrage=Refresh

- The rolling resistance of a bicycle is 0.008 (this is typical of utility bikes and mountain bikes with semi-slick road tyres).

7.5.2 High level issues arising from the census dataset

High level issues (see Table 7.1) arose when constructing the census constraints: Age of data (temporal differences) and deliberately introduced errors are discussed below. There were also issues of ensuring data consistency in terms of attribute definition. Attempts to deal with this issue were discussed above. Not all issues were completely resolved. The simplification of allocation of bike availability related to NSSEC is not an ideal solution. However, it is useful to try to include some consideration of socio-economic factors in the likelihood of having access to a serviceable bicycle immediately following a fuel shock. When the constraint tables were built, the 2011 census data was not available so the 2001 census was used. Whilst accepting this as a limitation, the 2001 data illustrates the application of the method. Additionally it would be relevant to compare changes between the 2001 results and results using 2011 data. Deliberate errors in the census were considered. The solution adopted, adjusting the table cells to ensure all table totals were consistent has been used by other researchers,.

7.5.3 Further issues with census data

Commute distance was assumed to be uniformly distributed across each distance bin: If an individual is allocated a commute distance bin of 2-5km, they have the same probability of 2.1km, 3.5km and 4.9km commutes. In reality, geography influences the distribution of commute distances within a bin. A hypothetical example illustrates the point: A town is in the hinterland of a city. There are many commutes across the town up to 6km. There is also a rural area approximately 10km wide to workplaces in the city. There are many journeys that are approximately 16-20km but very few in the 10-15 km range as shown in Figure 7.16. This shows the limitation of having a uniform distribution. The areas affected are those where the inter-urban distance across the rural area is sufficiently short to allow inter urban commuting. The effect on the model will be to suggest that some individuals have a shorter commute than in reality. It may in these cases falsely increase the indicator score. There are many other hypothetical examples. In each example, the most appropriate distribution of commutes within each bin is different. If the model were being implemented at a smaller extent, allowance could be made for this phenomena, but to include it in a national extent model may increase the complexity to a point where it runs too slowly on a PC to be effective.

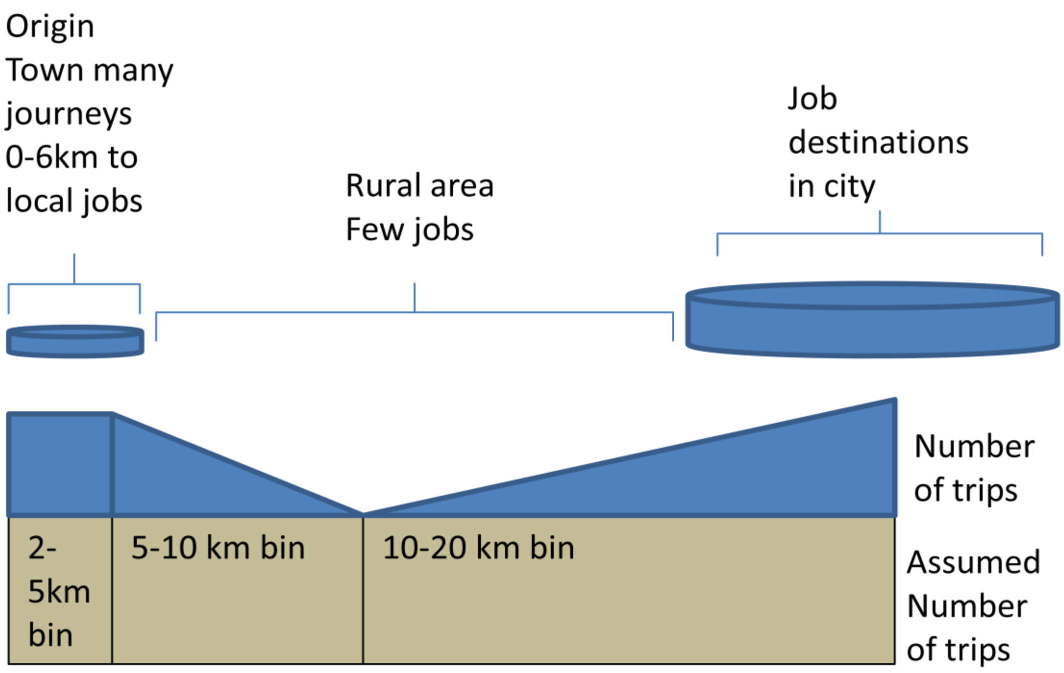

Figure 7.16 The actual distribution of trips in blue versus the assumed distribution of trips in grey for a hypothetical town in the hinterland of a city.

7.6 High level issues arising from the Health Survey for England (HSE) data

There were temporal differences between datasets. The HSE dataset was collected in 2008, whereas the census was collected in 2001. The rate of change of obesity was less between 2001 – 2008 than it was from 1995 – 2001 (NOO, 2014). Though it would be ideal to have all data sets from the same year, this does not appear critical in this case.

The subgroup of 1754 respondents described in Section 7.3.3 though all based on measured data, was deemed too small. A sample population which is too small creates a poor representation of people with attributes at the extreme of the distribution (Birkin and Clarke, 2012; Edwards and Clarke, 2012; Huang and Williamson, 2001). In this case it did not include people with more extreme values for of VO_{2max} and BMI. In short, it did not include subgroups which are known to exist in the real population and which have an effect on ability to commute by active modes[38]. Secondly there

[38] The HSE testing protocol prohibited individuals taking part in the test on such criteria as obesity and having a heart condition (Craig et al., 2009).

were a large number of constraint combinations which were empty. Adding the sub-group of 113 people classed as “very unfit” went some way to including obese and unfit people in the sample. This still lacked variation and many constraint cells remained empty so the 9246 subgroup was added. As described above, the estimates of VO_{2max} whether modelled or gathered from step test data have variation about their estimates so Monte-Carlo sampling was used to represent that variation. The sample population of 111128 appears to meet the main criteria for being a suitable sample population. It is improved in the following ways: It is much larger than the population of an individual Output Area; contains acceptable measures or estimates of unconstrained variables; contains the full range of unconstrained values which one would expect to find across the population as a whole. In terms of the indicator scope the sample population of 111128 appears capable of showing variation between areas and between base case and policy case situations.

7.6.1 Issues arising from constraints

The level of constraint is high. There are 46 individual attribute categories giving 9600 possible combinations. There are 11,100 individuals in the HSE micro-data which were useable in the generation of the sample population. Because this is not a great deal larger than the number of constraint combinations there are empty cells. This will have some effect on the quality of the internal goodness of fit of stage 1 of the spatial microsimulation. It also suggests there will be higher levels of error in very atypical areas (Cassells et al., 2012; Edwards and Clarke, 2012).

7.6.2 Issues arising from gradient

The gradient given to an OA is based on the 5km x 5km cell its centroid sits in shown in Figure 7.14. A 5km x 5km cell covers much of the residents’ immediate neighbourhood though it is unlikely to cover the average gradient for all entire journeys. However the average gradient across a 5km x 5km cell will be similar to the average gradient in the neighbouring cells in the majority of cases. An arbitrary decision had to be made about cell size for gradient. 5km is the maximum distance pedestrians could travel in the model, though many cyclists could travel further.

7.6.3 Issues arising from NTS data

NTS data is used in the allocation of bike availability. As discussed in Section 7.4.4.1, the socio-economic aspect of estimating bicycle availability is an approximation. NTS data are also not temporally consistent with all other data sets; 2009 and 2010 data were used. There is however little difference in values compared to 2008 the year from which the HSE data is taken. Whilst acknowledging the inconsistency this is not regarded as critical.

7.6.4 Issues with rolling resistance.

Rolling resistance varies depending upon the type of tyre fitted to a bicycle. The biggest influence on rolling resistance is the tyre profile itself (tyre pressure and rider weight also have an effect). A wide knobbly mountain bike tyre has a greater rolling resistance than the smoother thinner tyres found on a utility bike, which in turn has higher rolling resistance than a road racing tyre (Wilson, 2004). Data is available for rolling resistance of different tyres (Morse, n.d). Parkin et al., (2008) suggest that approximately 60% of the UK bike fleet may be mountain bikes or 'bike shaped objects' with knobbly mountain bike tyres. Data on the socio-demographic split of the UK bike fleet by type is not freely available. It is reasonable to hypothesise that the types of bicycle available to different segments of the adult population may differ based on age, gender, socio-economic attributes and possibly geography. The simplifying assumption was made that all bikes had utility bike tyres. Another option would have been random allocation of bike type to each individual who has a bike. This would not have accounted for the hypothesised variation in bike type and tyre availability across the population. There is a danger that had random allocation been used it could introduce stochastic 'noise' which would mask the effects of other attributes. Whilst using a simplifying assumption acknowledges a limitation in model accuracy (it will lead to an over estimation of the indicator in some areas) this is better than undermining the understanding which can be gained from assessing the effects of the other variables.

7.6.5 Issues with wind speed

The wind speed estimation is very much an approximation. Firstly, it is the mean wind speed for an entire year. It will vary greatly from day to day. Secondly, due to turbulence, eddies, funnelling and many complex movements of air around obstacles, localised wind speeds and direction will vary greatly. Thirdly, this calculation does not account for wind direction. In the model $h_{1.2}$ taken from equation [7.3] is assigned as the headwind. A rider may not be riding into the headwind at any point in their commuting day due to shift in wind direction during the day. The opposite may also be true. It is also possible that a rider will ride into a headwind for an entire leg of the journey (there or back). This is the simplifying assumption. As the model assumes that a person will not exceed a particular effort threshold based on exercise domains discussed in Chapter 5.6, they cannot be assumed to ride harder on one leg of the journey but take it easy on the other leg. Finally, the roughness length is set at 0.4 for the whole country. It varies considerably, but a more precise estimation was not practical at such a wide extent. However choosing this category is most likely to represent residential areas. Most residential areas in the UK are nucleated settlements in rural areas and low rise suburbs in urban areas.

7.7 Data conclusion

Reflecting upon the data sets used, some were easy to choose based on suggestions from literature and reports of their previous use such as census data. The principal datasets chosen: the Health Survey for England and the UK census are judged acceptable due to their wide spread use in previous research and evidence of robustness in their user documentation. The attributes within them are measured or collected directly from surveys. The attributes they contain are needed to calculate the indicator. The preparation of data for spatial microsimulation attempted to deal with the high level issues listed in Table 7.1. Allocating some attributes was problematic. There were attributes which required data to be teased out of several sources (in the case of the need to escort) and approximated (in the case of bicycle availability). This unfortunately makes the data specification for the model rather complicated, and cannot be guaranteed to be free from errors. These problems arise from trying to use existing secondary data sources not designed for this purpose, to try to gain new insights into the spatial distribution of features of the transport and mobility system. However, despite imperfections in data processing and limitations in data availability and compatibility, sufficient progress has been made to contribute to objective 3: A range of secondary data sources from England have been integrated, so it is possible to report results at both fine and coarser geographies. The results from this case study are examined in Chapter 8 to validate the modelling process.

8 Indicator validation

8.1 Introduction

This chapter is concerned with validation of the modelling process. The modelling process was explained in Chapter 6 and its application to the case study of English Output Areas explained in Chapter 7. Specifically this chapter is about validating the modelling process, its application and what that implies for using the model output as an indicator of adaptive capacity to fuel shocks. Validating the modelling process contributes towards developing a 'good indicator' as defined by Marsden et al., (2006) (see Section in 3.3.3.2). This chapter will contribute to objective 3:

> *Test the applicability of the design and methods to real data. This will be achieved by integrating a range of secondary data sources from England to report results at both fine and coarser geographies (Output Areas*[39] *and coarser geographies in the UK hierarchy).*

Model validation and sensitivity testing involves ensuring that the model in question is an accurate enough representation of the real world to be useful for its application. If the level of error and uncertainty is sufficiently small that the phenomena of interest can still be seen, then the model in question remains useful. (Box, 1987; Sargent, 2011; Schlesinger et al., 1979; Tukey, 1962). This applies to quantitative models in general not just spatial microsimulation and spatially explicit indicators. Model validation and sensitivity testing is also an important precursor to the interpretation of results, as it informs policy makers of the amount of caution which must be applied to a specific result. Unlike aspatial models, validation of spatially explicit models also highlights the specific locations where errors are large.

Validation of the modelling process developed in Chapters 5 – 7 involves:

> *Carrying out validation tests on the spatial microsimulation which were described in Section 5.4.3* (*referring to for example* Edwards and Tanton, 2012; Voas and Williamson, 2001; Williamson, 2012)*.*
> *These tests examine similarities between the synthetic and real populations. If they are similar enough, the synthetic population can be regarded as representative of the real population.*

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[39] Output Areas are the smallest spatial units used for dissemination of aggregate UK census data. Further information is given in Chapter 5.

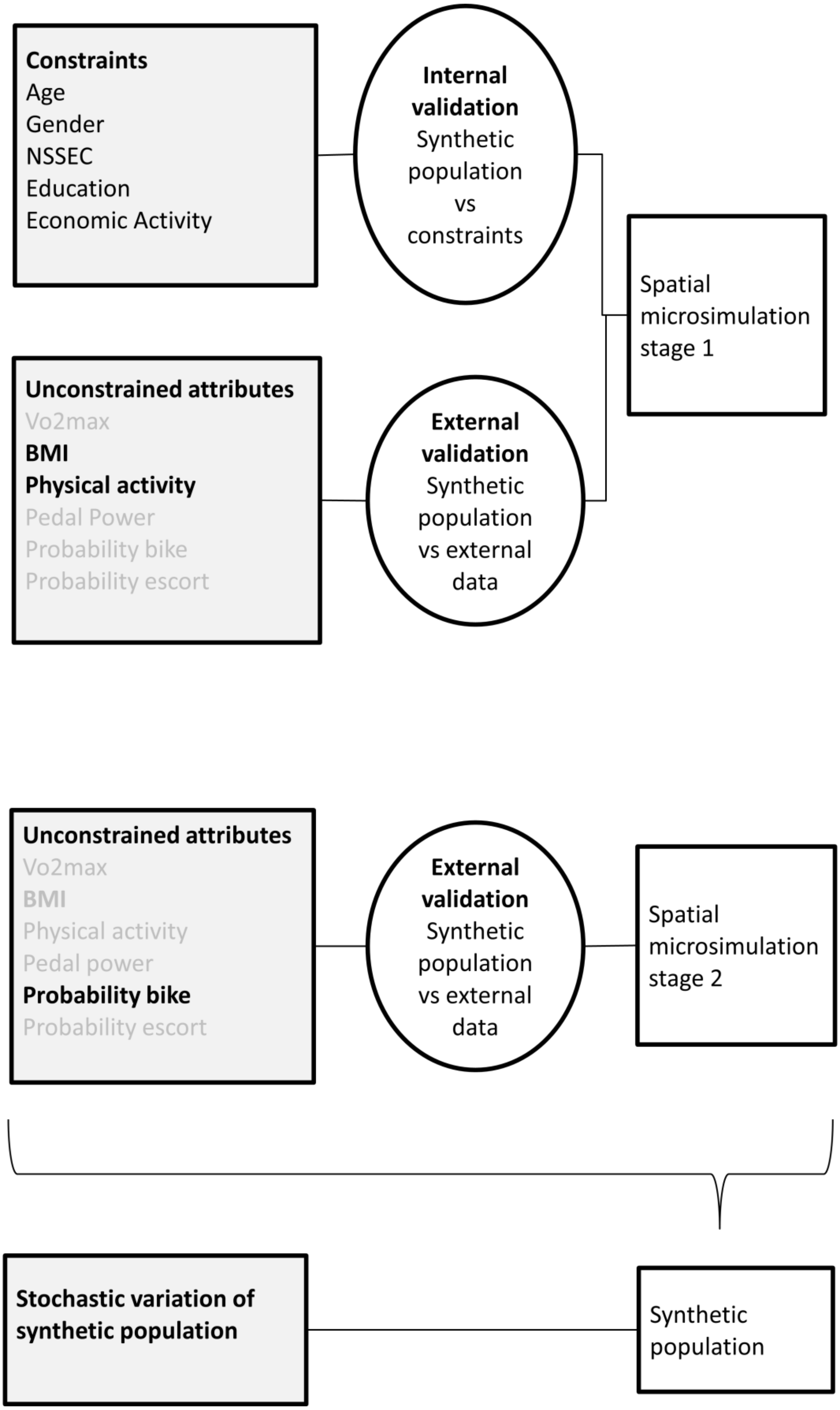
Carrying out sensitivity tests. These tests look for evidence that the model results are not excessively influenced by the simplifying assumptions of the modelling process.

The chapter is structured as follows: Section 8.2 describes internal validation tests performed on the microsimulation (these techniques were discussed in Section 5.4.3). Section 8.3 discusses external validation tests on the spatial microsimulation (these techniques were also discussed in Section 5.4.3). Section 8.4 examines the sensitivity of the model to simplifying assumptions. Section 8.5 summarises the results of validation and sensitivity tests to determine the following: The overall level of error and uncertainty and what this implies for using the model output as an indicator of adaptive capacity to fuel shocks and whether the modelling process is likely to be able to identify variation between locations and between the base case and policy case. If this is the case it suggests that the methods and data used are suitable for calculating the indicator.

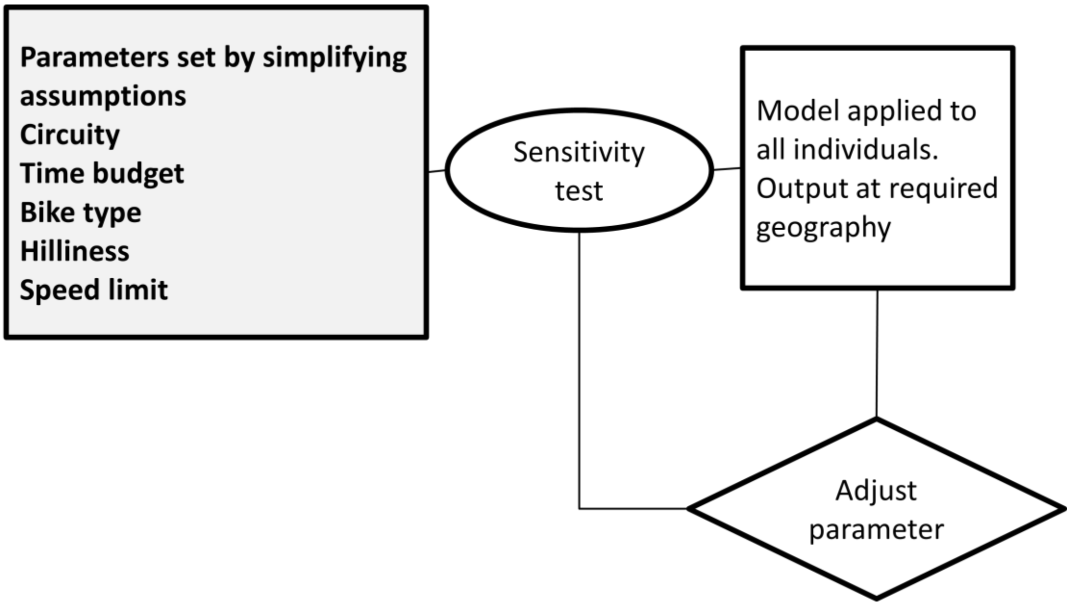
The validation of the synthetic population attempts to assess the extent to which the synthetic population is a realistic representation of the actual population (Tanton and Edwards, 2012; Voas and Williamson, 2001). Internal validation tests constrained attributes; those common to both the constraint tables and the sample population (e.g. sex and age). First the synthetic population is aggregated to the same resolution as the constraint tables, in this case Output Areas. Measures then test the extent to which the constrained attribute matches the constraint table count for that attribute (ibid.). This is also called validating the internal goodness of fit (Harland et al., 2012). If a synthetic population has a high goodness of fit is one piece of evidence that suggests the synthetic population is representative of the real population. An overview of the tests carried out on the spatial microsimulation is shown in Figure 8.1a.

External validation evaluates the fit of unconstrained attributes; those found in the sample population but not in the constraint tables (for example Body Mass Index BMI). However, as explained in Section 5.4.3, external validation of spatial microsimulation models is very difficult (See for example Tanton and Edwards, 2012). This is because the reason for using spatial microsimulation in the first place is a lack of data covering all the attributes of interest at the spatial resolution and extent required. This means that there is usually little or no data available to validate against. External validation tests of stage 1 of the spatial microsimulation are carried out on BMI and physical activity. The fit of stage 2 of the spatial microsimulation is examined by testing correspondence of bike availability in the synthetic population with national estimates of bicycle availability.

Sensitivity tests are carried out on inputs to the model which are based on simplifying assumptions (see Figure 8.1b). The effects that these simplifying assumptions have on indicator values is tested. Sensitivity tests checked the following: assumptions of the reduction in time available for commuting caused by needing to make escort trips, assumptions about the types of bicycles available to people, assumptions about slope profile, assumptions about the maximum downhill speed of a cyclist and assumptions about circuity.



(a) Validation of part 1 of the modelling process: internal and external validation of spatial microsimulation



(b) Validation of modelling process part 2: sensitivity testing

Figure 8.1 Overview of indicator construction and validation processes

(a) Validation of modelling part 1: spatial microsimulation. (b) Validation of modelling process part 2: sensitivity testing. Attributes tested are highlighted bold.

8.2 Internal validation (testing internal goodness of fit) of stage 1 of the spatial microsimulation.

The methods of internal validation discussed in Chapter 5.4.3 were used. Firstly scatter plots were made. These give a quick and simple representation of the degree of fit between the synthesised attribute and the Output Area count for the attribute (used by for example; Lovelace and Ballas, 2013). The second method of internal validation is to examine measures based on Total Absolute Error (TAE) (used by for example; Harland et al, 2012). It is a simple error assessment of the number of misclassifications of a constraint. To give a measure of the statistical significance of errors, z scores and Z^2 scores were used to assess the fit of cells and zones (used by for example; Williamson, 2012). The range of tests was picked to get an overview of errors, and examine both absolute and statistical errors in more detail. As noted in Section 5.4.3 there are a number of validation techniques which are in use, but no formally accepted standard procedure (Tanton and Edwards, 2012). These tests were used on a subset of the results to reduce computing time. One percent of Output Areas were selected. Every 100th Output Area was selected. The whole population in that Output Area was tested. The sample covered all regions of the country.

8.2.1 Internal validation 1 : Scatter plots

The synthetic population was aggregated to Output Area resolution. It was then compared to the constraint tables (census aggregate data). Constraint table cell counts were plotted against synthetic population cell counts. Differences between constraint and synthetic population cell counts are seen as deviations from the y=x line on the plot. The errors shown on the scatter plots are total error, note that errors are double counted. This can make errors seem larger than they actually are Figures 8.2 – 8.5 below show that there is virtually no error in the education, and limiting long term illness constraints. The sex by age by economic activity constraint shows that small errors are more common with many points close to but not exactly on the line. There are also a small number of points with larger error. Errors are visibly larger with the NSSEC constraint; these can be seen in Figure 8.5. The constraints education, LLTI and sex by age by economic activity have a good fit overall. NSSEC does not appear to be well fit overall. The “unable to classify” category has a large influence on this because as explained in Chapter 7 there were no individuals with the NSSEC “unable to classify” category in the sample population, but this category does appear in the census.

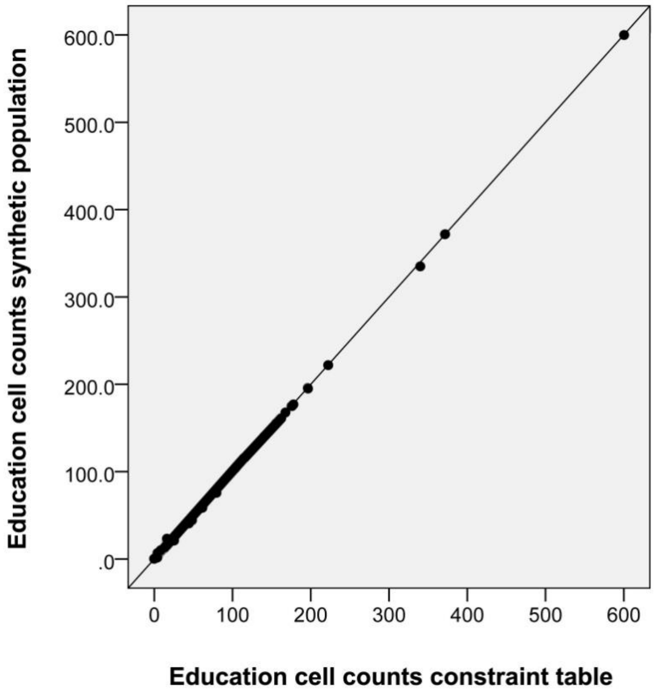


Figure 8.2 Constraint table count versus synthetic population count for all education categories.

There is virtually no deviation from the x = y line suggesting a very good fit.

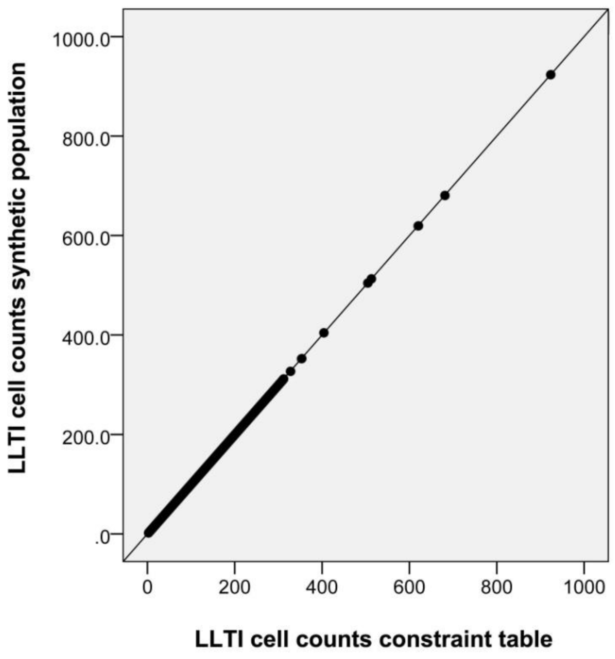


Figure 8.3. Constraint table count versus synthetic population count for both LLTI categories.

LLTI appears to have a perfect fit. As this is a univariate constraint with only two categories, it is "easy" for the algorithm to get a perfect fit. It shows that the sample population contains individuals in both categories.

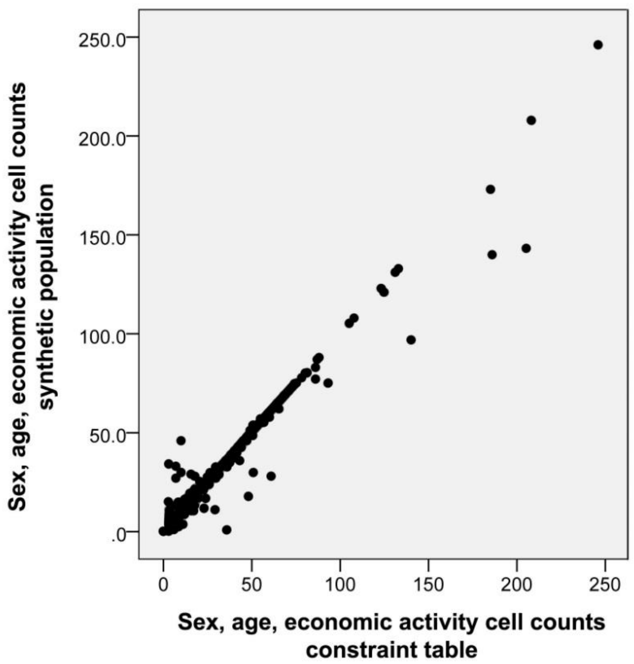


Figure 8.4. Constraint table count versus synthetic population count for all sex, by age, by economic activity categories.

There is one Output Area with a total error of approximately 50. There also appear to be approximately 20 (~1% of Output Areas in the validation sample) which are some distance from the y=x line. The vast majority of the OAs in the validation sample have a good fit.

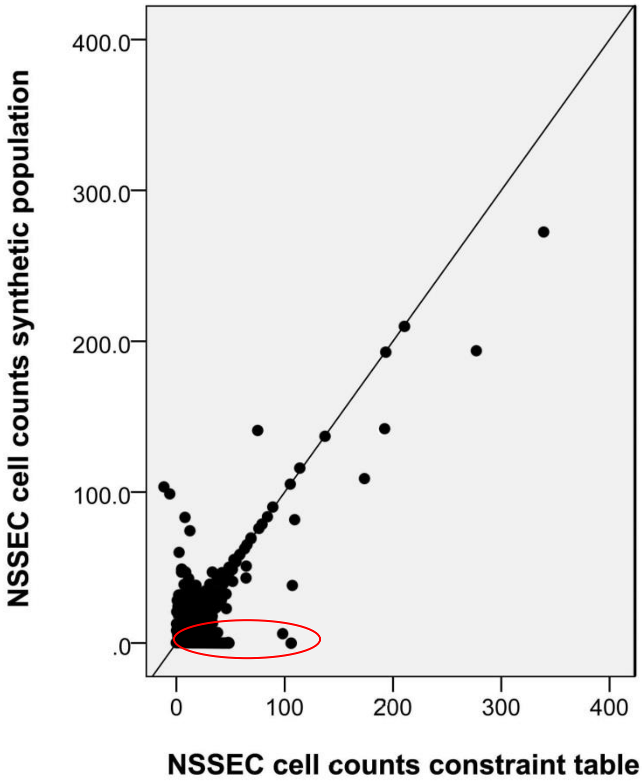


Figure 8.5. Constraint table count versus synthetic population count for NSSEC categories.

Though the majority of points appear on or close to the y=x line, there is larger error with NSSEC. The highlighted points fall in the 'cannot be classified category'. This is because there are no individuals in the sample population with this characteristic whereas in reality there are people with an unclassifiable NSSEC in many Output Areas.

The purpose of the scatter plots is to identify any problem cases. They have highlighted a limitation in the data sources. Specifically there is a limitation caused by the construction of the NSSEC constraint. Therefore the way to address it is to explore the different ways of building the constraint and examining what effect it has on the indicator result. This is discussed in the coming sections.

8.2.2 Internal validation 2: TAE based measures of fit

The errors observed in the scatter plots can be summarised numerically using Total Absolute Error or a measure such as Percentage Cell Error which contextualises total error in terms of population size. From Chapter 5.4.3 recall that in calculating TAE, *T* is the simulated population cell count and *E* is the expected cell count (the constraint table value). Subscripts *i* and *j* denote the cell's position; *i* is the i^{th} attribute category and *j* is the code for the Output Area.

$$TAE = \sum_{i}\sum_{j}\left|T_{ij} - E_{ij}\right|$$

[8.1]

Cell percentage error is derived from TAE and takes account of population.

$$CPE = \frac{(TAE)}{population} \times 100$$

[8.2]

TAE double counts errors. It counts an error in both the cell which has over counted and in the cell which has under counted (Harland et al., 2012; Voas and Williamson, 2001). Commonly TAE /2 is used and referred to as the classification error. From this the percentage classification error PE is derived which gives an indicator of the proportion of the population misclassified:

$$PE = \frac{\left(\frac{TAE}{2}\right)}{population} \times 100$$

[8.3]

Table 8.1 Percentage classification Error (PE) derived from Total Absolute Error (TAE)

Constraint attribute	**PE**
Limiting long term illness	0
Education	0.007
Sex by age by economic activity	0.51
NSSEC by sex	9.2

8.2.3 Internal validation 3: z and Z² scores

The worst performing constraint NSSEC by sex has a Percentage Classification Error (PE) of 9.2%. Further analysis is useful to assess the level of fit. As was explained in Chapter 5, z-scores can give an indication of whether the synthesised constraint is significantly different to the constraint table data (Voas and Williamson, 2001; Williamson, 2012). As explained in Section 5.4.3, the percentage classification error, whilst useful does not calculate whether a difference between constraint attribute count and OA count is statistically different (Williamson, 2012). A z score is calculated for each cell by the FMF spatial microsimulation software using the equation shown below:

$$z_{ij} = \frac{(t_{ij} - p_{ij})}{\sqrt{\frac{P_{ij}(1 - P_{ij})}{N_j}}}$$

[8.4] Copy of equation [5.4] (Williamson, 2012 p32).

The z score test is a commonly used test in spatial microsimulation validation (Edwards and Tanton, 2012). In the z score test, a z score of less than 1.96 suggests that a cell in the aggregated synthetic population is not significantly different to a cell in the constraint table. NSSEC Categories 1 – 3 have a good fit with over 95% of Output Areas having z-scores less than 1.96 in these cells. Virtually all OAs had z scores over 1.96 for the category 'cannot be classified'. Between 20 and 40% of cells in categories 5 – 8 had a poor fit. This suggests that category 'cannot be classified' is being redistributed mainly amongst NSSEC categories 5-8.

To assess the overall fit of the NSSEC by sex constraint, a Z^2 score test was performed. It is another test described and used in the spatial microsimulation literature (e.g. Huang and Williamson, 2001; Voas and Williamson, 2001; Williamson, 2012). A Z^2 score was calculated for each zone and compared to Chi-squared critical value tables. A Z^2 measure was taken to summarise the fit of the constraint for all categories for each Output Area. Z^2 was calculated as follows: Z^2_j is the Z^2 score for Output *Area j.* Z_{ij} is the z score for the *ith* constraint cell in Output Area *j.*

$$Z_j^2 = \sum_i \left(Z_{ij}\right)^2$$

[8.5]

In equation 8.6, *C* is the critical value on a Chi-squared table given the number of degrees of freedom (the number of categories in a constraint minus 1). Output Area *j* has a good fit if Z^2_j is smaller than *C.*

$$Output\ Area\ jGood\ fit \quad = \begin{cases} 1 & Z_j^2 \leq C \\ 0 & Z_j^2 > C \end{cases}$$

[8.6]

Z^2 scores were calculated from the z scores using equations 8.5 and 8.6. The Z^2 scores were calculated on a zone by zone basis. There are 19 degrees of freedom when analysing the 20 categories in the NSSEC by sex constraint. Where Z^2 scores were below 30.1435 for a given Output Area, the NSSEC constraint was not significantly different from the synthetic population (which indicates a good fit). By this measure however, only 43% of Output Areas were a good fit on the NSSEC constraint.

8.2.4 Improving internal goodness of fit

There is a balance between error and fidelity of the model. Error being the error values such as TAE or PE described above and fidelity being the amount of detail about individuals the spatial microsimulation is trying to represent. A higher fidelity comes from having more constraint categories. Higher fidelity is more likely to have error, but to reduce that error may require a reduction in fidelity. The 20 category version of the NSSEC constraint aimed for higher fidelity, but there were errors (as can be seen in the scatter plot in Figure 8.5 and the error test calculations). It is a logical approach to see what happens if the fidelity is reduced whilst trying to reduce the error.

A second version of the NSSEC was constructed. This version had only 3 categories. The internal goodness of fit measures are included in Table 8.2 They are clearly an improvement on the error measures above.

Table 8.2 Internal goodness of fit using a 3 category classification of NSSEC.

Variable Name	**TAE**	**PE**	**Z sores indicating poor fitting cells**
Sex by age by economic activity	453	0.065177	0
Education	453	0.065177	0
LLTI	455	0.065465	0
NSSEC with 3 categories	453	0.065177	0

The indicator was then calculated for the two populations, one with 20 categories in the NSSEC constraint and 1 with 3 categories using the 1 percent sample of Output Areas described above. Figure 8.9 suggests the outputs are similar.

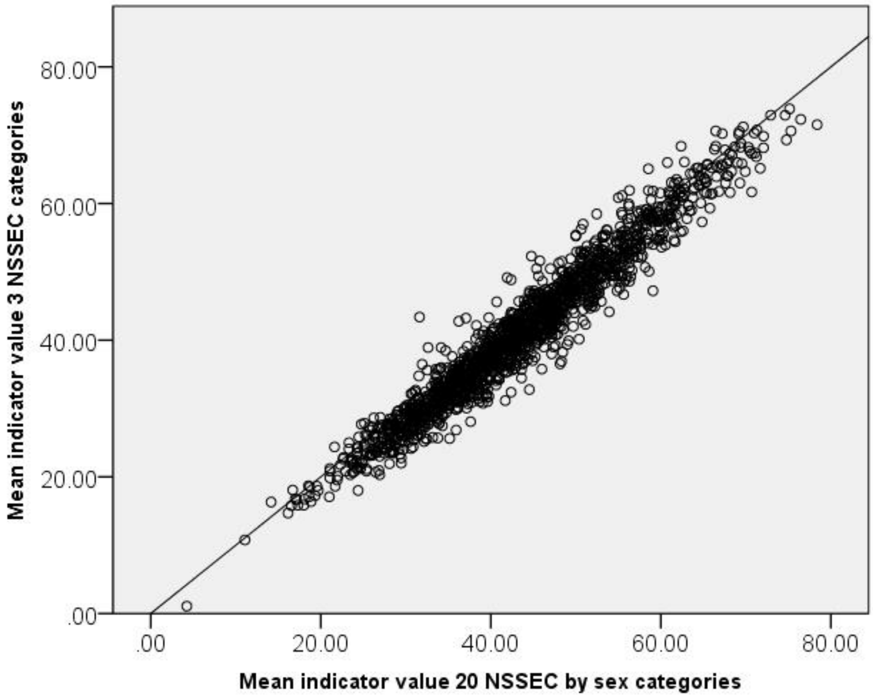


Figure 8.6 Comparison of indicator values for NSSEC with only 3 categories and a 20 category NSSEC by sex constraint.

The mean indicator result for all zones with the aggregated 3 category NSSEC is 2.37% lower than the results using a 20 category constraint.

Table 8.3 Comparison of the indicator result using different constructions of NSSEC constraint.

	Population with 20 NSSEC by sex categories	**Population with 3 NSSEC categories**
Mean	43.56	41.19
Standard deviation	4.03	4.04

15% of output areas had an absolute difference in the indicator value of more than 5%. Only 0.6% of Output Areas had greater than 10% difference in indicator results.

The 3 category NSSEC constraint table was built as follows: Category 1 grouped together NSSEC 1 & 2, category 2 NSSEC 3 & 4, Category 3 NSSEC 5-8. The students and unable to classify categories in the constraint table were allocated to categories 1 – 3 based on the frequency of groups 1-3 in each zone as suggested in (Cassells et al., 2012).

With the 20 category NSSEC by sex constraint, the Simulated Annealing algorithm in effect allocated an NSSEC category to people who were identified in the census as “cannot be categorised”. What is being done follows the same principle in both cases – estimate the NSSEC of people in “cannot be categorised” based on the other attributes of the people in that zone. It does not seem instantly clear that one method is superior to the other.

On the basis of internal goodness of fit measures, the population with only 3 NSSEC categories performs better having lower error. This would be reason to reject the original synthetic population and use one with the amalgamated three category constraint. However, aggregating the constraint has a small effect on the indicator result in most areas. It can also not be assumed from internal validation that the amalgamated constraint gives a synthetic population that is more representative of the real population. In order to test that, external validation tests are needed.

8.3 External validation

Three external validation tests were carried out assessing the BMI, physical activity and bicycle availability attributes. Though VO_{2max} could not be tested, the fit of BMI and physical activity may be used as a proxy for the fit VO_{2max}. There is some justification for doing this as BMI, physical activity and VO_{2max} are correlated. This can be seen in the HSE data and is explained in Section 5.7.1 .

8.3.1 Stage 1: BMI; modelled obesity versus Health Survey for England data

Public Health England produced a national estimate of the level of obesity. The estimates were based on Health Survey for England data from 2006 – 2008 (PHE, 2013). The validation is not completely external data in the strictest sense as it contains the 2008 HSE data used to construct the sample population. It is the best available data though so is used on that basis. These measures were compared with the synthetic population produced in the spatial microsimulation and summarised in Table 8.4.

Table 8.4 Comparing obesity levels in the synthetic population to Health Survey for England data to assess the fit of the BMI attribute

Variable	**Proportion of the population who are obese %**
PHE national estimate (HSE data 2006 – 2008)	24.2
1% sample of synthetic population with 20 NSSEC categories	23.9
1% sample of synthetic population with 3 NSSEC categories	23.5

Public Health England also produced a district level estimate of obesity levels based on the same data for which they were given access to the location of each respondent. The synthetic population was also aggregated to district level to make comparison with the PHE district obesity measure. 315 of the 326 English districts were compared as shown in Table 8.5.

Table 8.5 Percentage of districts where synthetic population estimate of obesity was within the 95% confidence interval of the Public Health England (PHE) district resolution estimates

Variable	**% of districts in PHE confidence interval**	**Root Mean square Error (RMSE)**
District resolution synthetic population with 20 NSSEC categories	54%	2.6
District resolution synthetic population with 3 NSSEC categories	57%	2.3

The following estimates how much the error in classifying obesity affects the indicator. The indicator was calculated with sample population with 1754 individuals who completed a step test. These individuals were not obese. The mean indicator value when this sample population was used was 50%. The mean indicator value calculated using the full sample population of

111128 (see Chapter 7 for further details) was 43%. The full sample population included people with a wider range of BMI values. This suggests that a 100% reduction in obesity would yield a 7% change in indicator value. The difference in indicator value resulting from an error of 2.6% in the classification of obesity is likely to be of the order of 2.6 X (7% / 100) ~ 0.18%. The difference in indicator value attributable to the difference between obesity estimates in the two constructions of the synthetic populations is approximately 0.02%. To take the population with the aggregated NSSEC constraint and claim it produces a more accurate indicator value with such small attributable differences would be a weak claim. The effect that this has on later analysis is as follows: It highlights uncertainty caused by building the spatial microsimulation using different configurations. It also informs the analysis of the results in Chapter 9. The test using 1% of Output Areas indicates the range of variation caused by different NSSEC configurations. The same procedure used to test a 1% sample of the Output areas can also be used to measure the variation for all 165665 Output Areas in England. This information would give an indication of how robust the indicator is in every location.

The logical extension of this would be to build numerous synthetic populations: using large and small numbers of categories in each constraint; building the constraint tables using different univariate and cross-tabulated census tables and also building populations using candidate constraints rejected in Section 7.2. Following this it would be possible to take the results of all of these populations and examine the variation. This could be used to examine in more detail the relationship between fidelity and error. This however is beyond the scope of the current thesis. It may be of interest for future work. A basis for this might be work by Smith et al., (2009), who built several synthetic populations and allocated the most realistic synthetic population to Output Areas in Leeds and Bradford.

8.3.2 External validation: Synthetic population physical activity versus external data.

The Health Survey for England 2008 produced several measures of physical activity. One variable was “ad30spt”. This recorded the number of occasions in the last 4 weeks that the respondent had done 30 minutes or more of sport. A similar indicator is produced by the Sport England Active

People Survey called the 1x30sport indicator[40]. This is a measure of those participating in a sport with a Sport England related National Governing Body once a week for thirty minutes or more. The AD30spt and 1x30 measures are similar but not identical. Table 8.6 shows that at a national resolution there is close correspondence between the proportion of people not participating in any sport according to the APS, the HSE and the synthetic population. This gives some small evidence of validity – though the percentage difference cannot be used as a precise measure of model error. This is because the measures are not exactly the same. Table 8.6 also shows only a small difference (0.2%) between the populations built using the different NSSEC constraint configuration. Therefore this suggests that on this attribute, changing between the two NSSEC configurations has little effect. Referring back to Figure 7.12 (box plot of vigorous exercise by NSSEC), the finding was that the high NSSEC groups exercised more frequently than lower groups. Amalgamating adjacent categories which were similar may have little effect on the indicator.

Table 8.6 External validation of physical activity

Variable	**Proportion of the population** **With no participation in sport**
APS 1x30sport	57.0
HSE ad30spt	58.5
Sample population	57.5
1% sample of synthetic population with 20 NSSEC categories	58.7
1% sample of synthetic population with 3 NSSEC categories	58.5

8.3.3 Stage 2 : Bicycle availability

The bicycle availability attribute was added in the second stage of the spatial microsimulation using Monte-Carlo sampling. The synthetic population was

40 Data available at:
http://archive.sportengland.org/research/active_people_survey/active_people_survey_3.aspx

aggregated to national level. The proportion of those with a bike was measured. This was tested against the national bike availability figure from the National Travel Survey as shown in Table 8.7. There is just over 1% difference. Also of interest is the relative difference in bike availability between the two NSSEC configurations. When the synthetic population using the 3 category NSSEC constraint was tested the difference was 3.6%. This suggests that aggregating the constraint categories has caused a reduction in representativeness. Excessive amalgamation of attribute categories can reduce representativeness of the synthetic population (Müller and Axhausen, 2010; Voas and Williamson, 2001) as explained in Section 7.4.3.4.

Table 8.7 Bike availability. Comparison of National Travel Survey data with the synthetic population.

Variable	**% of adult population with use of a bike**
NTS 2010 national estimate of bike availability amongst adults.	37.2
Synthetic population 1% sample Using 20 category NSSEC by sex constraint	38.3
Synthetic population 1% sample Using 3 category NSSEC constraint	33.6

8.3.4 Summary of comparison between populations with different configurations of the NSSEC constraint

Both constructions of the synthetic population were well constrained on sex, age, economic activity, education and Limiting Long Term Illness. NSSEC was a good fit in the population where NSSEC was aggregated. In the external validation tests the population with 20 category NSSEC by sex constraint performed marginally better than the 3 category NSSEC population. There is not enough evidence to reject the population with the 20 category NSSEC by sex constraint and simply use the population with the 3 category NSSEC constraint. As stated above and in Section 7.4.3.4 amalgamating categories in a constraint table increases internal goodness of fit, but can reduce the representativeness. In this case retaining all the categories in the NSSEC constraint negatively affected the internal validation measures, but the effect on the indicator was small. In addition to the 1% sample of OAs used for validation tests, the base indicator was calculated for all zones using both constructions of the NSSEC constraint. In 95% of Output Areas the difference in indicator value between the two synthetic populations was less than 5.1%. Also only 0.6% of OAs differed by more than 10%. Rather than assuming one synthetic population is correct and the other is wrong, the testing is useful to highlight the 5% of areas where the indicator result is less certain.

In general, the unconstrained attributes of both synthetic populations were found to correspond adequately to the external data used in the external validation. A perfect fit with unconstrained attributes is not possible (Voas and Williamson, 2001). The validation tests using two constructions of the synthetic population might have seemed a bit cumbersome. However it has been useful because it has given more insight into the uncertainty present in the synthetic population. This contributes to an indicator which is methodologically transparent.

8.3.5 Stochastic variation and uncertainty of the synthetic population

The Simulated Annealing algorithm used in stage 1 is a probabilistic means of Combinatorial Optimisation. Williamson (2012) tested 100 replications of a spatial microsimulation using Simulated Annealing and Synthetic Reconstruction techniques. The fit of the former was both better and the level of variation in quality of fit was very small. So even though Simulated Annealing is a probabilistic technique, Williamson (2012) states that with a Simulated Annealing based synthetic population only a single synthetic population need be created. This assertion appears to have become accepted practice. Applications and tests of Simulated Annealing have also used a single synthetic population (Harland et al., 2012; Hermes and Poulsen, 2012).

The second stage of the spatial microsimulation involves Monte-Carlo sampling. Because it uses Monte Carlo sampling, multiple draws are required. This introduces a level of stochastic variation which needs to be considered. Large numbers of draws allow a more robust estimate of the indicator. However this has to be traded off against the computation time to run a modelling process which takes a long time to run (Running the entire modelling process for the whole of England involves several days run time on a desktop pc).

To test the minimum number of draws which can be used, tests were done on the one percent sample of Output Areas described above, to examine the sensitivity of the model to the number of draws. If too few draws are used, the change in mean indicator value is large each time another draw is added. If enough draws are made, the change in mean indicator value is small when another draw is added.

The grand mean indicator value ($\bar{G}$) is the sum of the mean indicator value for each $\bar{A}_j$ zone *j* divided by the number of draws *N:*

$$\bar{G} = \frac{\sum_j \bar{A}_j}{N}$$

[8.7]

Figure 8.7 shows that the variation in $\bar{G}$ between 10 draws and 11 draws was very small; less than 0.04%. Additionally, the gain in accuracy gets smaller with each extra draw. In practice, this means that 10 or more draws would be acceptable because reporting differences of 0.04% would be regarded as spurious accuracy (An output area has an average working population ~130. An increase in indicator value of 0.04% would suggest 0.05 more people could get to work, which is meaningless).

The standard error of the mean for each zone, SE_j, was also examined. A small SE_j indicates a low level of stochastic variation in zone *j* and therefore greater certainty about the indicator value. SE_j is calculated by dividing the standard deviation between draws, sd_j of the indicator value for each zone by the square root of the number of draws *N.*

$$SE_j = \frac{\sigma_j}{\sqrt{N}}$$

[8.8]

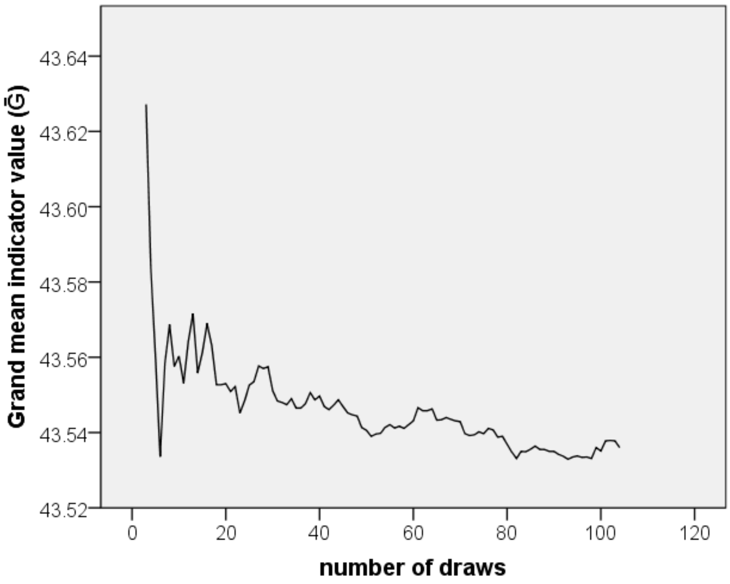


Figure 8.7 Variation in the grand mean indicator value (Ḡ) for 1 to 100 draws .

The variation in Ḡ between 10 draws and 11 draws was very small; less than 0.04%. This suggests that 10 draws would be acceptable because reporting differences in indicator values of 0.04% would be spurious accuracy.

The standard error of the mean for each zone SE_j was averaged across all zones to give $meanSE_{allzones}$.

$$meanSE_{allzones} = \frac{\sum_j SE_j}{N}$$

[8.7]

$meanSE_{allzones}$ is plotted in Figure 8.8. As the number of draws increases $meanSE_{allzones}$ decreases. It decreases dramatically after a small number of draws. After 13 draws (the number of draws used with the full population) $meanSE_{allzones}$ = 1.04.

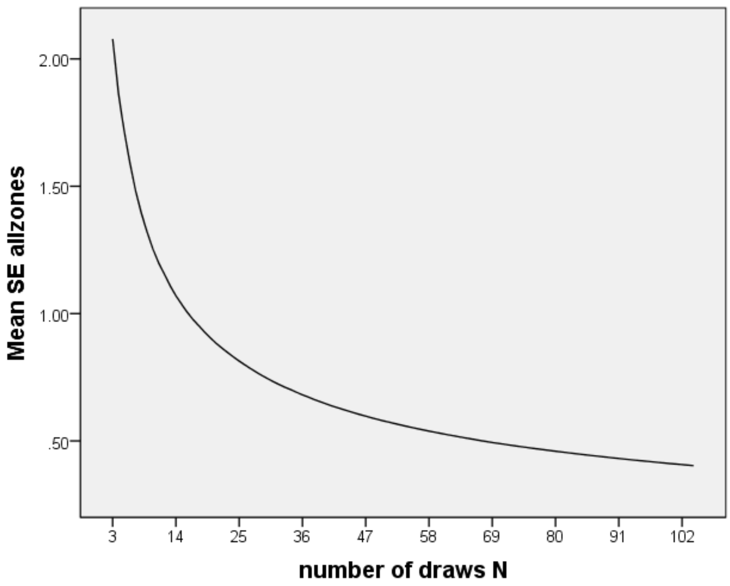


Figure 8.8. The standard error of the mean indicator value averaged across all zones to give $meanSE_{allzones}$ over 100 draws.

The range of values for standard error of the mean for each zone, $SE_{j,}$ is shown in Figure 8.9. 95% of zones have a standard error of less than 1.7%.

In addition to the stochastic variation, the uncertainty identified when simulating the population using different constructions of the NSSEC constraint should also be considered, to give an overall estimate of spatial microsimulation error. This can be estimated as follows: The indicator value in 95% of OAs varies by less than 5.1% when comparing the different constructions of the NSSEC constraint. The stochastic error estimated at 1.7% in Figure 8.9 is included within this. This gives an overall spatial microsimulation error of 5.1%. The standard deviation in indicator values is almost double this (11.41). This suggests that it will be possible to identify variation between the majority zones. It will be possible to identify zones which have extremely high or low indicator scores. This is useful because areas with extreme scores will be of particular interest to policy makers.

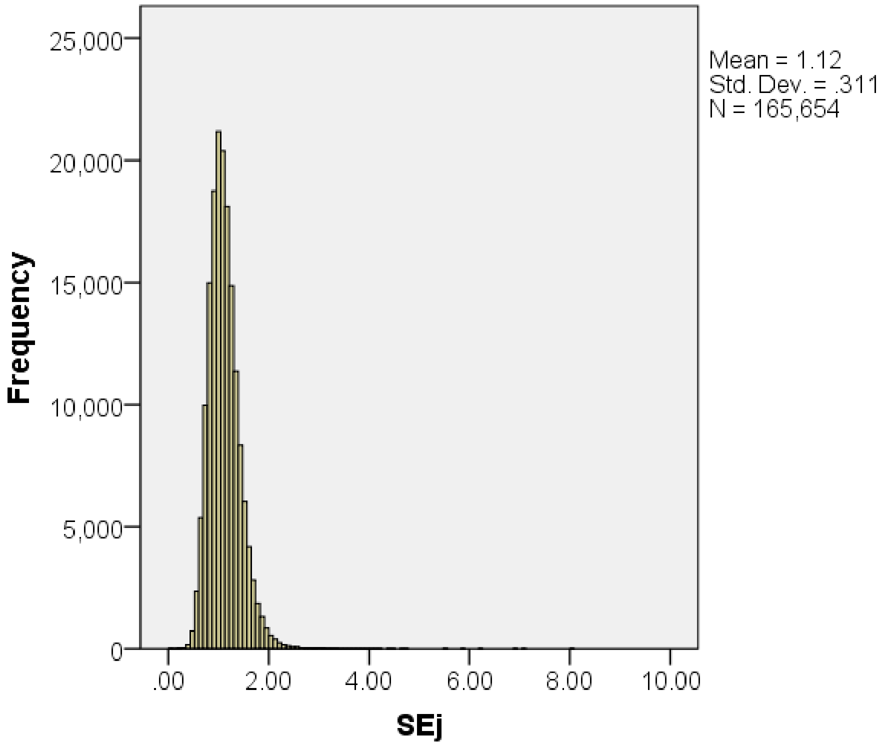


Figure 8.9: Variation in standard error of the mean between zones

95% of zones have a standard error of the mean of less than 1.7%.

8.4 Sensitivity of the indicator to simplifying assumptions

8.4.1 Time costs of escort trips

The simplifying assumption was made that the need to escort a child would reduce the amount of time available for commuting. In a further simplifying assumption, the travel time budget for those escorting was halved; from 1 hour to 30 minutes. The influence of these assumptions on the indicator was tested. Table 8.8 shows that at a national resolution the sensitivity of the indicator to increasing or decreasing the time taken to escort children is 1.17%. 70% of OAs tested are not significantly affected by a change in escort time; the indicator value for 15 and 45 minutes escort time was within the confidence interval of the indicator value with 30 minutes escort time. In addition 95% of Output Areas have a difference in indicator value of less than 2.4% if the escort time is changed. Therefore this suggests +-2.4% is a suitable estimate for the level of uncertainty caused by this simplifying assumption.

Table 8.8 The effect of changing the time penalty attributed to escort trips

Time cost of escorting children	**Mean indicator value with a 1% sample of Output Areas**	**% of OAs within the 95% confidence interval of the indicator with 30 minutes escort time**
15 minutes	44.56	87
30 minutes	43.53	(both: 70)
45 minutes	42.23	78

8.4.2 Sensitivity to hilliness

The maximum distance value is sensitive to gradient. There are many ways of estimating the slope encountered by the population of each area on their commute to work. There are two aspects to assumptions about hilliness:

- The assumption of the gradient encountered
- The assumption of the slope profile of routes taken

8.4.2.1 Gradient

The model has been calculated using three methods of estimating gradient. Methods 1 and 2 below were used in sensitivity tests. Method 3 is the method which used in the case study. It is described in more detail in Section 7.4.5.

Method 1: Previous literature on modelling propensity to cycle to work (Parkin, 2004; Parkin et al., 2007a) used a digital elevation model with a 1km resolution (the LCM2000 dataset[41]). The data used by Parkin contained mean orthogonal gradient (see Figure 8.10) between 50x50m cells within the 1km LCM model. The model in method 1 was calculated with a version of the LCM2000 digital elevation data which only had the mean height of each 1km grid cell and the mean fall line gradient. The gradient between these mean elevation cells was more gentle and less rough than the actual land surface as illustrated in Figure 8.11. This generated an underestimate of the slope encountered by pedestrians and cyclists; it smoothed the gradient likely to be encountered by walkers and cyclists.

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[41] Access to the data which was commissioned by DeFRA is through http://www.landmap.ac.uk/

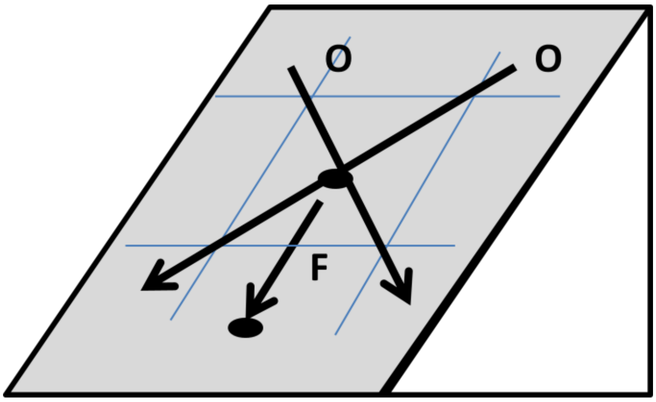

Figure 8.10 the fall line (F) and orthogonal lines (O) a basis for calculating gradient in a raster grid

The fall line is the steepest gradient between a cell and any of its 8 neighbours. This is the standard slope calculation employed by GIS packages such as ESRI ArcGIS (ESRI, 2011). The orthogonal gradient is an alternative method taking the mean of the slope between the two pairs of orthogonal cells.

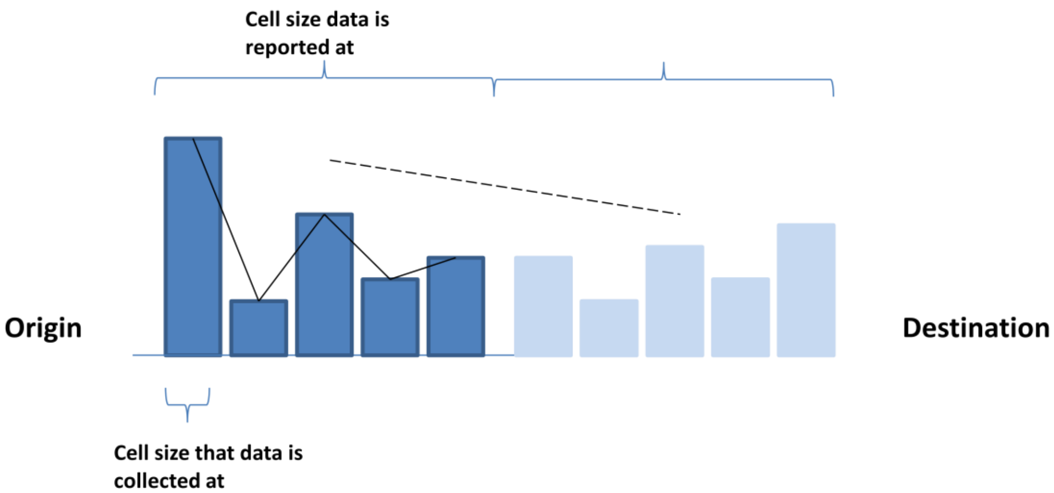

Figure 8.11 The effect of reporting gradient at a coarser resolution than data is collected at.

When the slope value is calculated as the difference in mean elevation between the coarser cells, the slope is smoothed (dashed line). This produced the gradient in method 1. When the slope is the mean of the slope between each high resolution cell that data is collected at the slope is steeper as shown by the solid line. This produced the gradient in method 2.

Method 2: To emulate the LCM2000 mean gradient data, the openly available SRTM (Shuttle Radar Topography Mission[42]) digital elevation data was processed as explained in Chapter 7. The fall-line gradient was

[42] Accessed via www.landmap.ac.uk

calculated for 75m cells. Cells with a gradient of over 33% were excluded. This is because the steepest Sections of roads in the most mountainous areas of England have a gradient of approximately 33%. The mean fall line gradient was calculated by aggregating the gradient of individual cells. This means of calculating gradient leads to an over estimate of the gradient encountered by cyclists and pedestrians. This is because roads, tracks and cycle routes frequently avoid the fall line. This method of gradient estimation would therefore be expected to produce an under estimate of indicator values. This can be seen in Table 8.9.

Method 3: As explained in Chapter 7, the Ordnance Survey Meridian2[43] data set and the STRM digital elevation data was used to calculate the mean gradient of every segment of road, and track in England. The mean gradient of network segments within 5km X 5km cells was then calculated. This method would be expected to give a more accurate estimate of the gradient experienced by walkers and cyclists.

Table 8.9 Mean Output Area gradient and indicator value given gradient calculation method.

Note the same slope profile was used in each of these tests; profile 3 from Table 8.10.

Gradient calculation method	**Mean Output Area gradient %**	**Mean indicator value for 1 % Output areas**
1	1.38	41
2	4.37	32
3	2.28	43

8.4.2.2 Slope profile

The slope profile is a two dimensional representation of the journey. Height is on the vertical axis and the distance from the journey origin on the horizontal axis. It shows the proportion of a journey spent going uphill, along the flat and downhill. It also shows the gradient of journey segments. Table 8.10 shows a range of possible slope profiles. The model knows only the origin and commute distance of commuters. Because destination and direction are not known, it is not possible to correctly plot the slope profile of

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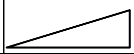
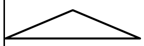
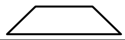
[43] Accessed via www.digimap.ac.uk.

every traveller. Because of this, the slope profile of travellers must be assumed based on the gradient around the origin zone.

Table 8.10 Possible slope profiles.

There are an infinite number of possible slope profiles but the simplest forms are shown. An example travel time is given for a rider on a utility bike with 100W Pedal Power, 95kg bike and rider, and 2% gradient on a 5km route.

	1	2	3	4	5		∞
Slope profile						…	
Cycle travel time seconds	574	1800	1471	1499	2300		

A clearly understandable simplifying assumption is that commuters travel uphill on one leg of their commute and downhill on the other. The uphill leg of the commute determines maximum distance. In this case the slope profile is assumed to be uphill for the duration of the journey. However a small test showed that this is unlikely to be the case for most journeys. 37 routes from 11 cities in England were plotted in different directions crossing the city centres. A total of 443 km of route was covered. (the data is shown in appendix 8.1). None of the routes were uphill or downhill in their entirety. There was a large range in distance between peaks (The greatest difference observed between changes in slope was 12km, the smallest 0.2km). The mean distance between a change in slope (from either flat to not flat, or uphill to downhill) was 1.6km. The distance between peaks was approximately 3.1km. The mean maximum travel distance was 4.94km using gradient calculation method 3. Maximum travel distance is greater than the mean distance between change in slope and also greater than the mean distance between peaks. It suggests that most commuters will have journeys which include uphill and downhill sections. This method of estimating slope profile will not be able to account for differences in height between origin and destination without information on the relative heights of all origins and destinations. Even so, across the population in all areas it appears a more appropriate simplifying assumption to choose a slope profile with up and downhill segments. Therefore considering slope profile in the study area reduces one source of error in the indicator.

8.4.2.3 Sensitivity to speed limit assumptions

Downhill speed limits were considered when the assumption was made that cyclists would have both up and down hill segments on their commute. This is in-line with the indicator scope; assuming that the maximum journey distance is safe for non-experienced cyclists. 25km was considered first. A higher limit and no limit were also considered. To test sensitivity of the indicator to speed limit assumptions it was calculated for the 1% sample of output areas described in Section 8.2. The indicator was calculated with a 25km/hr downhill speed limit and with no downhill speed limit. The difference in mean indicator value was 0.01%. No zones were found to be significantly different. Therefore the indicator is not unduly sensitive assumptions of how individuals control their speed.

8.4.3 Sensitivity to circuity

For ease of computation and based on the literature, circuity was set as 1.4. This was explained in Section 7.1.4.5. The indicator was tested for sensitivity to differing circuity values and is shown in Table 8.11. The mean effect of changing circuity by 0.2 was 1.31%. 95% of OAs differed by less than 2.9%. Therefore +-2.9% is a suitable estimate for the level of uncertainty caused by this simplifying assumption.

Table 8.11 Sensitivity of the indicator value to circuity

Circuity	**Indicator value %**
1.2	45.29
1.4	43.53
1.6	41.03
1.8	40.61
2.0	38.75
Mean difference in indicator per 0.2 change in circuity	1.31
95% of OAs differed by less than	2.9

8.4.4 Sensitivity to bicycle type

It takes more effort to go fast on a mountain bike with knobbly tyres than on a commuter bike with slick tyres. This is principally due to the variation in rolling resistance of different types of tyre[44]. As described in Section 5.7.4, a

[44] The riding position on a commuter bike is similar to a mountain bike so wind resistance is similar.

mountain bike tyre found on mountain bikes and 'bike shaped objects' typically has a rolling resistance of 0.036. A commuter bike with slick tyres has a lower rolling resistance of around 0.008. (Morse, n.d; Wilson, 2004) A rider bike combination of 95kg on a flat road pedalling at 100W output on a utility bike would travel 15.8km in an hour, but only 8.97km on a mountain bike. The effect of bike tyre type on the indicator is shown in Table 8.12. A simplifying assumption was made that all bikes have utility bike tyres. This simplification is explained in Section 7.5.8: Firstly, the national estimate of 60% of the bike fleet being mountain bike type bikes comes from only 1 source (Parkin et al., 2008). Secondly, there is no indication of the spatial or socio-economic distribution of bike type. For this reason it is left out of the indicator because it could introduce stochastic noise which would mask the effects of other attributes about which more is known.

Table 8.12 Sensitivity of the indicator to tyre type.

Assumed tyre type	**Mean indicator result for the whole population of 1% of Output Areas**	**Standard deviation**
All utility bikes	43.53	4.02
60% mountain-bikes	40.41	3.99

8.5 Validation and sensitivity testing summary

The estimate of error and uncertainty for the national mean base case indicator is +-4.85%. This is composed of 2.37% spatial microsimulation error, 1.17% sensitivity to the time cost of escort trips and 1.31% sensitivity to the assumption of circuity. The overall error and uncertainty for an individual Output Area identified by validation and sensitivity testing is estimated at +-10.4% or less in 95% of Output Areas. The components of the error and uncertainty are shown in Table 8.13. This value is far less than the range of indicator values, which suggests it should be possible to discern OAs with particularly high and low values. This will be examined in detail in Chapter 9. A practical output from this Chapter is Figure 8.12. It shows the estimate of error and uncertainty for all Output Areas. This will aid interpretation of results. The important finding of the tests carried out in this chapter is that they have applied techniques which can identify areas where errors may be larger and where the model is more or less sensitive, which contributes towards testing the applicability of the methods to real data as stated in objective 3.

Table 8.13 Summary of the level of uncertainty at Output Area resolution in the modelling process discovered by validation and sensitivity testing.

Attribute	**Maximum effect on indicator % in 95% of areas.**
Spatial microsimulation error and uncertainty	$\pm$5.1
Time costs of escort trips	$\pm$ 2.4
Effect of circuity (increase or decrease by 0.2)	$\pm$2.9
Approximate cumulative uncertainty in indicator value	$\pm$**10.4**

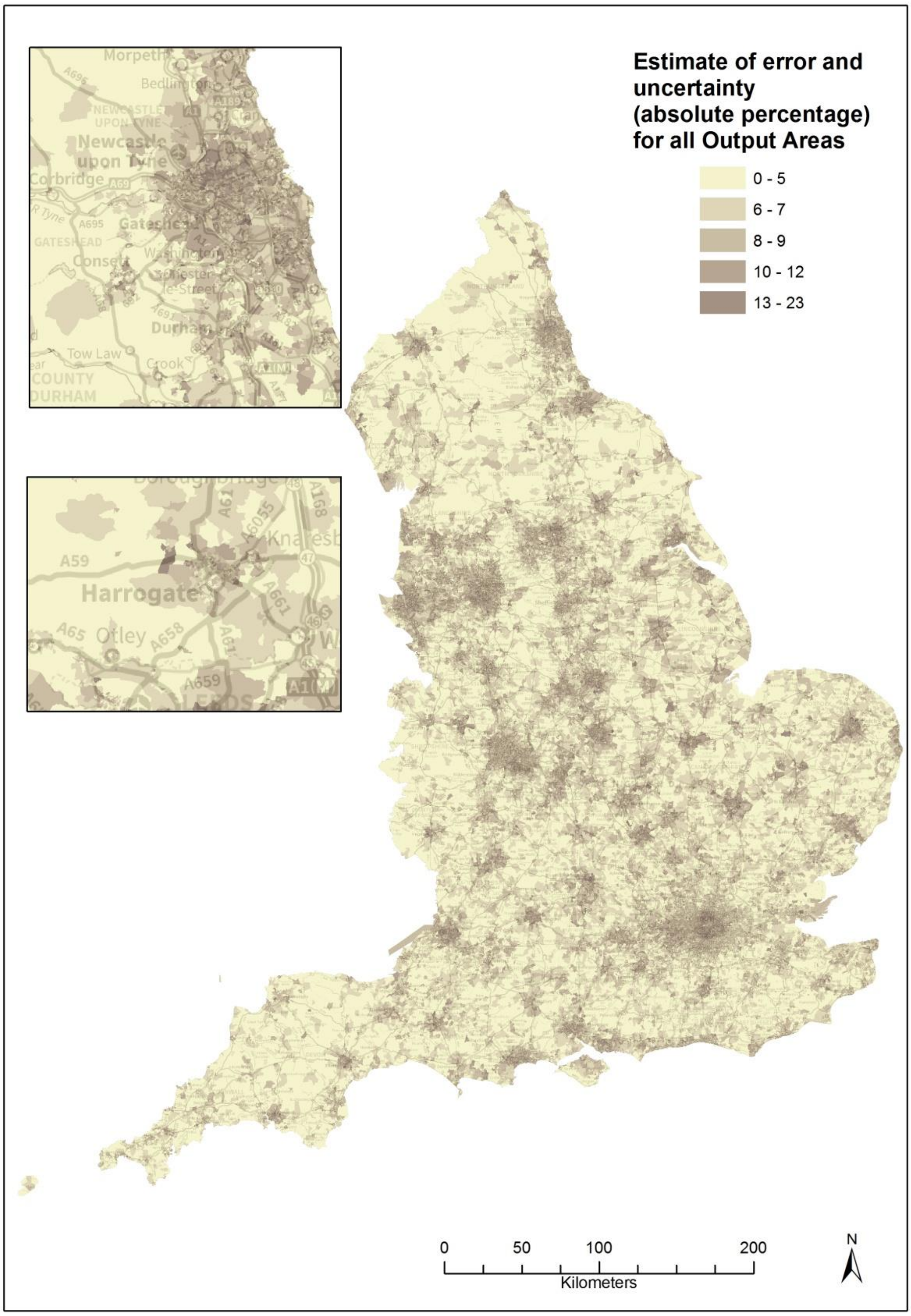


Figure 8.12 Estimate of error and uncertainty for all OAs

9 Analysis of results

9.1 Introduction

In the proceeding chapters a new spatially explicit transport policy indicator has been developed which shows who could get to work tomorrow by walking and cycling if there was a fuel shock today. This chapter contributes to objective 4:

> *Test the ability of the indicator to show variation between areas in both a base case and when specific policy measures are applied, and consequently report the effectiveness of the tested policies at increasing the resilience to fuel shocks by promoting adaptive capacity by walking and cycling.*

It is useful to briefly recap the reason why it is important to show variation between base and policy case *and* spatial variation. In transport planning, it is accepted that indicators have to be able to describe both a current situation and an alternative situation. This is so that comparison of alternative courses of action or progress over time can be measured. This idea was first discussed in Section 3.2.3. However, the development of spatially explicit modelling tools generates advances in the effectiveness of transport and social policy (Ballas et al., 2005b; Openshaw, 1995). This is because it allows more effective targeting of resources to people and places most likely to be vulnerable to fuel shocks. This idea was introduced in Chapter 1 and discussed in Section 4.2.1.

To address the objective, the following steps are taken. Firstly, in Section 9.2 the base case results for the indicator are shown as they are output from the modelling process. These are ‘raw results’ and if taken ‘at face value’ the reader could believe that all variation in indicator values are as a result of the different individual and geographical attributes. Doing this would give some information about the spatial distribution of adaptive capacity to fuel shocks. Something can be gained however by taking account of the findings reported in Chapter 8: By giving the policy maker some information about the level of error or uncertainty in the results, more informed decisions can be made; caveats about the results in particular areas can be given. It also illustrates to the researcher areas where better data may be sought, or as a start point for refining the methods.

In Section 9.3, tests are performed on the base case results. If the indicator is effective it will be possible to distinguish variation even when error and uncertainty is accounted for. For example, Output Areas with extreme results could be distinguished with a greater degree of confidence than simply taking the base case results at face value. Further analysis of the base case results are carried out in Section 9.4 where results are presented at different spatial resolutions.

Section 9.5 discusses a test of the ability to show the effect of policies at Output Area resolution. This also uses the findings of Chapter 8 to identify with a greater degree of confidence that a policy implemented in a particular Output Area would improve adaptive capacity to fuel shocks. This is a conservative estimate of the impact of a policy because conservative estimates present lower risks of under-performance for policy makers.

Section 9.6 tests the ability of the indicator to relate to wider issues. Transport policies have to be implemented within a wider policy making framework. Ramani et al., (2011) suggest that indicators which affect generic sustainability issues are more important than those only relevant to a specific domain such as transport. This is one of the criteria for good indicators discussed in Section 3.3.3.2. The results are placed in context of measures of deprivation and social classification in an attempt to identify the least resilient areas. Indicator results can also be presented at a local extent to understand a specific area in more detail. To do this, a more in depth study of Leeds local authority is presented in Section 9.7. Section 9.8 draws together the different outcomes from the results.

9.2 Raw results

If we ignore what we found in Chapter 8, we would take the results of the indicator ‘at face value’ and believe that we were seeing real world variation. We could accept Figure 9.1 below as a true representation of the indicator. Figure 9.1 is a cartogram. Cartograms distort maps to emphasise variables other than area (Dorling, 1996). The cartogram resizes OAs based upon the number of employed people resident in the OA producing the distorted images in Figure 9.1. The small, densely populated Output Areas found mainly in cities are increased in size. This gives a clearer impression of the proportion of the population with adaptive capacity to fuel shocks.

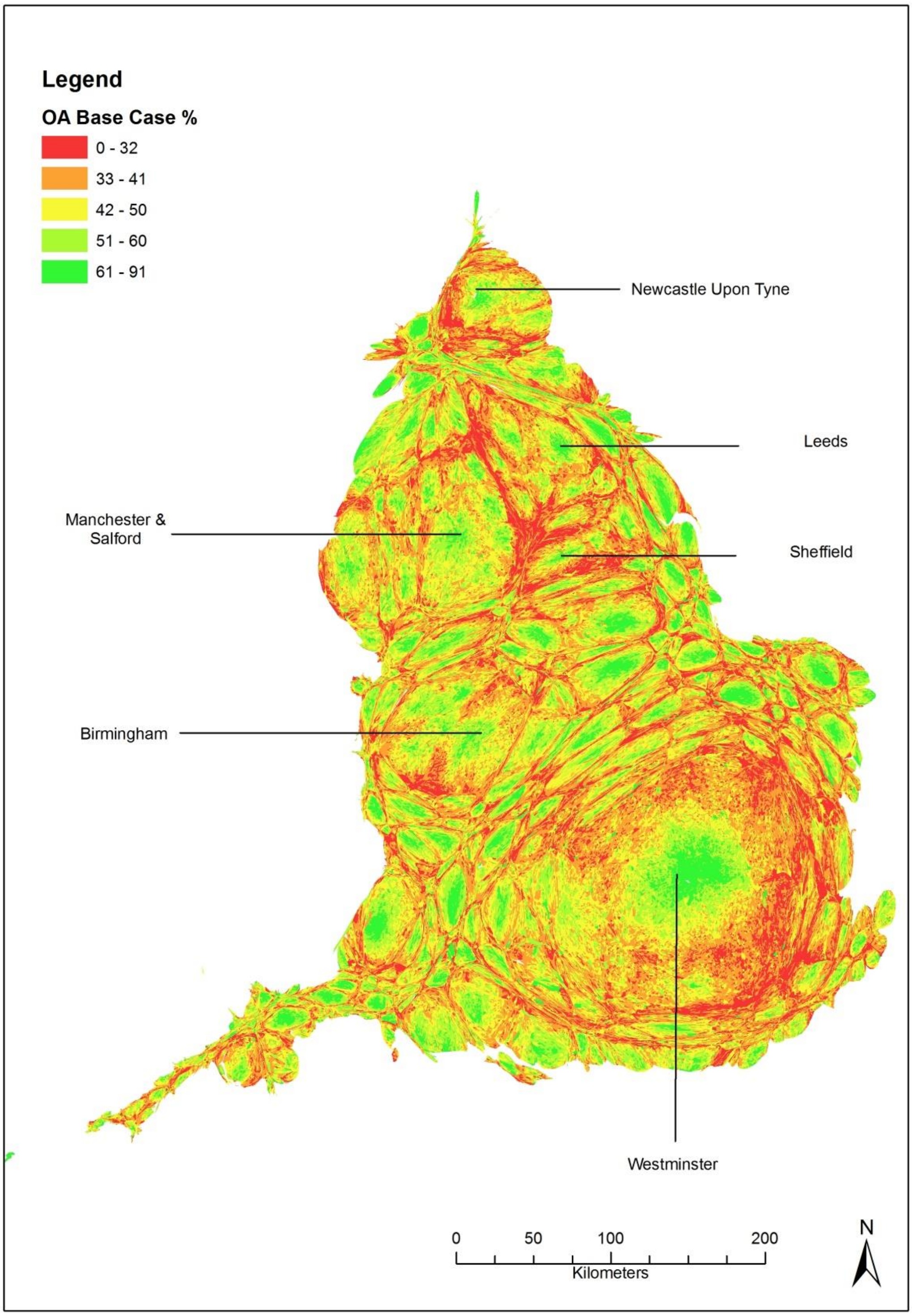


Figure 9.1 Output Area cartogram; 'raw' base case indicator values

Values are percentages of the number of people in each Output Area who could commute to work by walking and cycling following a fuel shock in a traffic network with no motor vehicles. OAs are resized based upon the number of employed people resident in the district. It emphasises populous OAs in urban districts. The Gastner Newmann method (Gastner and Newman, 2004) is implemented using an ARCGIS plugin. (ESRI, 2009).

If the findings from Chapter 8 were ignored, the following would also be possible. The results for the different OAs could be ranked. They could be split up into groups. The class boundaries could be drawn at standard deviations and by convention (see for example Field, 2013) we would accept that all the values more than 1.96 standard deviations from the mean are 'extreme'. Figure 9.2 shows a histogram of the base case results for all Output Areas. The red lines are + and – 1.96 standard deviations from the mean. It shows values below 21.28% to be extreme. However, without accounting for the findings from Chapter 8 there is a danger that these raw results would be misleading. Because of the error and uncertainty in the modelling process it is possible that in reality some OAs with a raw base case score below 21.28% have a higher score and in fact should not be thought of as extreme values. In order to present a 'good indicator' (see criteria in Section 3.3.3.2), it is important to share, with the reader of the thesis or the practitioner applying the indicator, information that helps them decide how much confidence they can have in a particular result and the level of caution they should apply to each result. The rest of this chapter identifies what variation can be observed when the findings of Chapter 8 *are* considered.

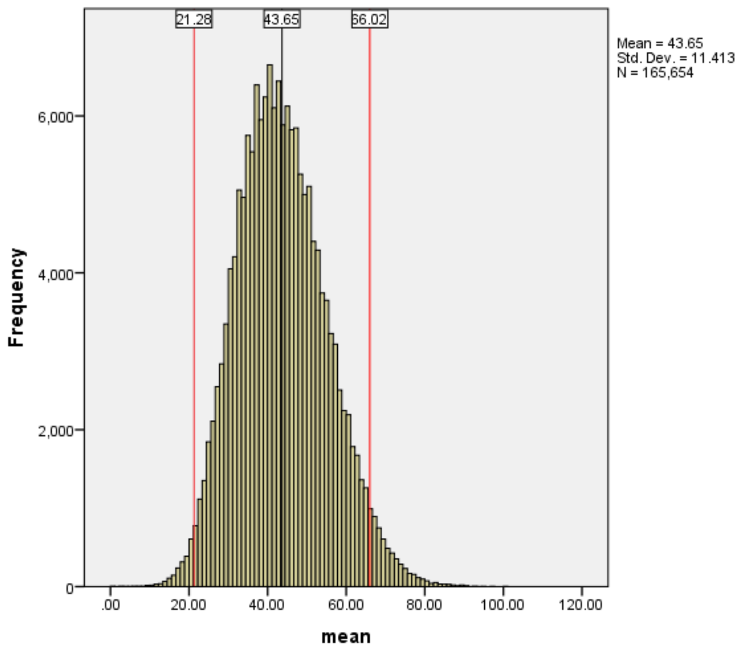


Figure 9.2 A histogram of raw base case results.

The red lines are at 1.96sd from the mean.

9.3 Testing the ability to show variation between base case results at Output Area resolution

9.3.1 Base case tests and rationale

The ability to show variation between base case results at Output Area resolution is tested by accounting for the effects of the error and uncertainty identified in Chapter 8 as follows:

Test 1: Output Areas are placed in the categories in Table 9.1 taking account of the error and uncertainty identified in Chapter 8 (see Table 8.13 for a summary).

Table 9.1 Categories into which OAs can confidently be placed.

Category	Criteria
Above national mean	National mean < OAmean - error
More than 1sd above national mean	National mean+ sd < OAmean - error
More than 1.96 sd above national mean	National mean+(1.96*sd) < OAmean - error
Below national mean	National mean > OAmean + error
More than 1 sd below national mean	National mean- sd > OAmean + error
More than 1.96 sd below national mean	National mean -(1.96*sd) > OAmean + error
Not significantly different from national mean	OAmean - error < National mean And OAmean + error > National mean

Test 2: The categories identified in test 1 are mapped. If the variation between OAs in test 1 form a pattern similar to the raw results this an indication of confidence in the general pattern of base case results. The rationale for these tests is firstly; presenting only the raw results would not have given an honest acknowledgement of the error and uncertainty identified in Chapter 8. Secondly, these tests are relatively straightforward. Thirdly, the results of the test are easily visualised and can be compared to the raw results.

Table 8.13 shows a summary of the error and uncertainty value for Output Areas. The error has also been estimated for each individual Output Area. The error consists of the spatial microsimulation error (which includes the stochastic variation and uncertainty) and the error attributed to sensitivity to simplifying assumptions. As both components of the error vary between Output Areas it has been estimated for each OA. This means that for those examining the indicator at a local level there is an estimate of the confidence in the result for each OA.

9.3.2 Base case test 1

63% of OAs can confidently be discerned as having above or below average base case scores when uncertainty is accounted for. Additionally the indicator is able to identify that 11% of OAs are more than one standard deviation from the mean and that 1% are more than 1.96sd from the mean (in the highest or lowest 5% of OA scores nationally). Even though in the latter category, the percentage of OAs identified is small, the absolute number of Output Areas identified is 1676. To put that in context it represents approximately 500,000 people. To be able identify this number of people and to highlight with spatial precision, concentrations[45] of particularly low and high levels of adaptive capacity aids targeting of resources by policy makers.

Table 9.2 Results of base case test 1: categories into which Output Areas can confidently be placed.

Category	Number of Output Areas	Percentage of total number of OAs
Above national mean	37005	22.3
More than 1 sd above national mean	7915	4.8
More than 1.96 sd above national mean	1042	0.6
Not significantly different from national mean	60690	36.6
Below national mean	48304	29.2

[45] Important note. OAs with low indicator scores have concentrations of people without adaptive capacity to fuel shocks. It does not mean *all* people in the Output Area are vulnerable (that would be to fall foul of the ecological fallacy).

More than 1 sd below national mean	10075	6.1
More than 1.96 sd below national mean	634	0.4

9.3.3 Base case test 2

The variation between OAs in test 1 form a pattern similar to the raw results. This is shown by comparing Figures 9.1 and 9.3. This suggests that the general pattern of base case results can be described with some confidence. High values are seen in the centres of urban areas. The indicator score decreases with distance from urban centres and appears roughly proportional to the size of the urban area. Accessible rural areas at the outer edges of the extended commuting zones have low values. Outer rural areas do not appear to have uniformly low indicator scores.

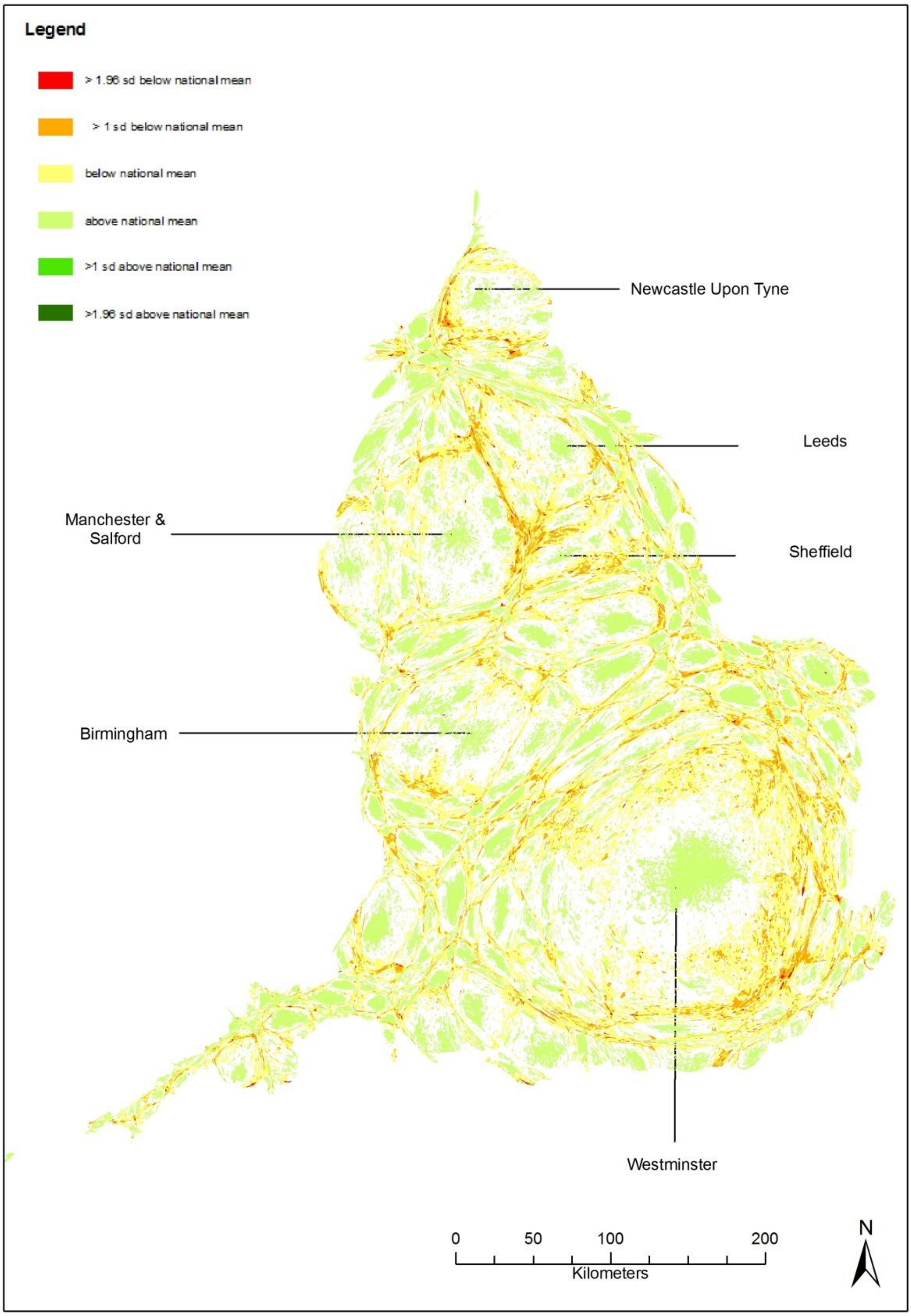


Figure 9.3 Output Area cartogram. Base case indicator values categories accounting for error and uncertainty.

9.4 Further analysis of base case results

Results are presented at different resolutions. The reasons for this are firstly to test the ability of the modelling process to report results at different resolutions. If OA results are heterogeneous across districts it is a demonstration of the need for fine resolution indicators. There are also practical reasons for presenting results at different resolutions. Firstly it makes a more useful indicator that is more flexible and easier to use; results can be made available in a format most helpful to planners and policy makers. It also makes users of the results more aware of the variation in the pattern of results at different aggregations. This reduces the risks of making policy decisions that fall foul of the ecological fallacy and Modifiable Unit Areal Problem (MAUP) (e.g. Horner and Murray, 2002; Openshaw, 1984). A second reason for presenting results at several resolutions is that coarse resolution results may be useful to contextualise fine resolution results. It is useful to be able to examine an OA indicator value in the context of both the national average and the district average.

The coarsest resolution results given is national; a single zone, England, with 21million working adults. Based on the raw results, only 44% of working adults in England could get to work by walking and cycling if there was no fuel available for motorised transport. Over 12 million people would have to change their working arrangements, change jobs, move home or commit other time or resources in order to adapt to a fuel shock. The consequences would have to be borne by employers, government, individuals, civil society or a combination of all four. The model reports that 25% of workers could get to work by bicycle and 17% by walking (that is a 60:40 split cycling: walking). Segmenting the population by age and gender in Figure 9.4 shows that 16-24 year old workers have the highest base case indicator score. Figure 9.5 shows segmentation by highest educational qualification. Those whose highest qualification is level 1 have a noticeably higher base case indicator score than other groups. The association between low qualifications, low income jobs and short commutes is documented. (e.g DfT, 2010; Lucas, 2012; Social Exclusion Unit, 2003).

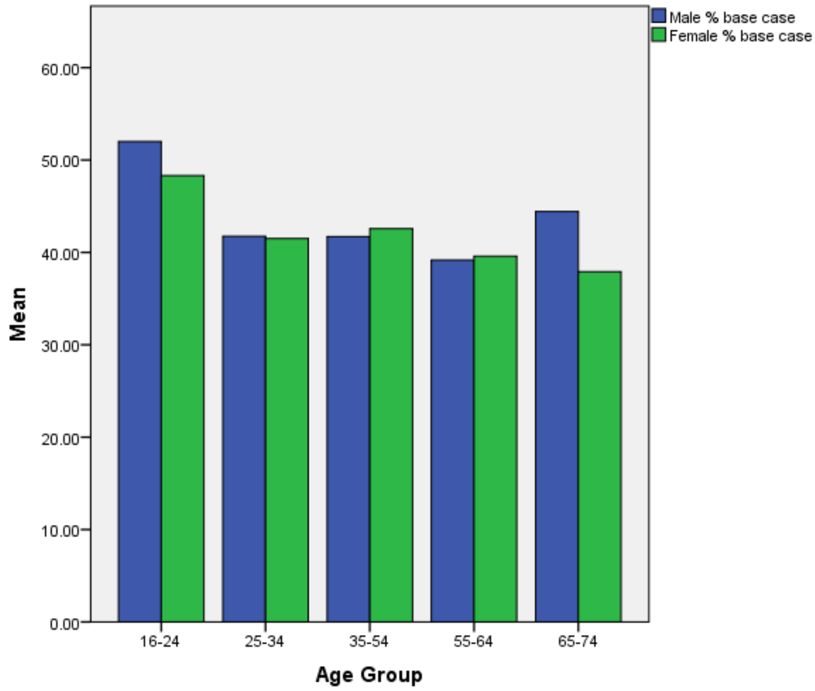


Figure 9.4 National base case indicator score by sex and age.

Note that these are raw results.

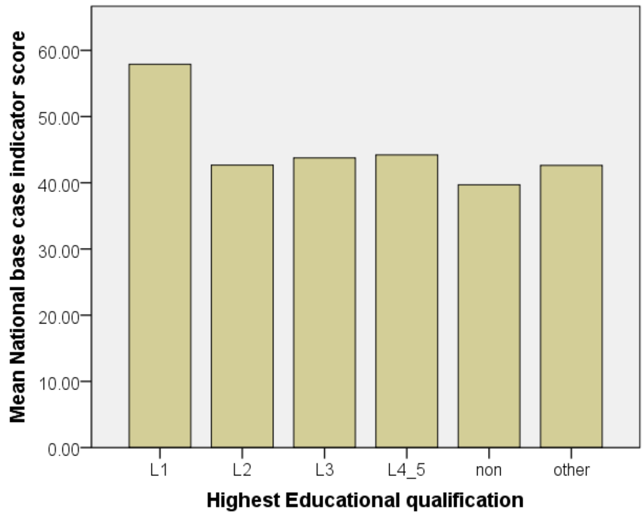


Figure 9.5 National base case indicator score by education

L4_5 is HND qualifications or above, L3 is A level equivalent, L2 is GCSE equivalent, L1is NVQ level 1 equivalent. 'Other' includes non-UK qualifications. Note that these are raw results.

9.4.1 Regional resolution base case results

England is divided into nine Government Office Regions. London, the East and South East have base case scores of 2-3% below the national average, whereas, the North West and South West are 2-3% above the national average. There are no strikingly large differences between the raw regional results. Figure 9.6 shows that The North West has 12.4% of Output Areas in the lowest indicator quintile and 23.3% in the highest quintile. The East Midlands, West Midlands and the South West also have higher proportions of OAs in the highest quintile of indicator scores. London has 9.5% more OAs in the lowest indicator quintile than the highest. The South East, East and Yorkshire and Humber have similar patterns to London. The OAs are binned by quintile nationally.

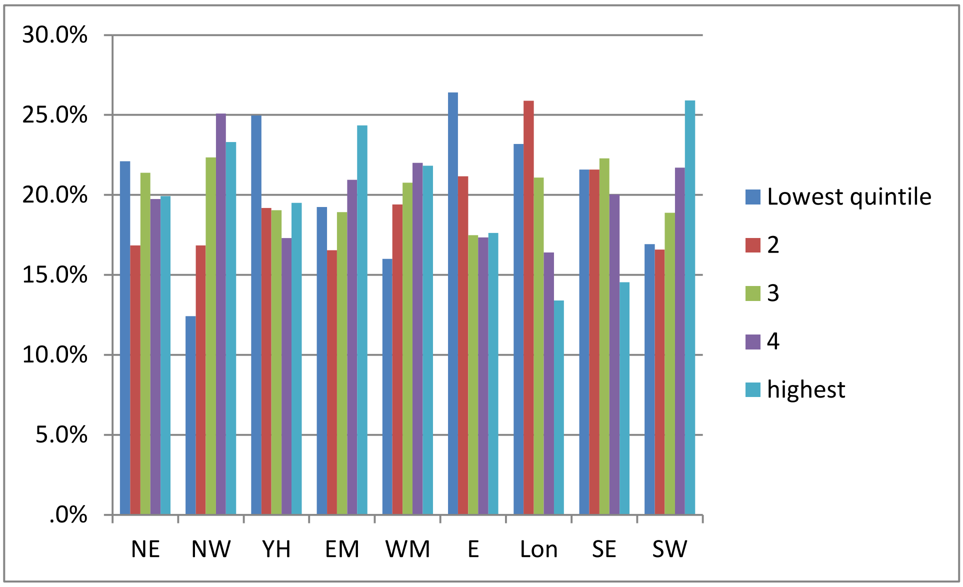


Figure 9.6 Base case results; indicator quintile by region

The proportion of a region's OAs which fall into each indicator quintile are shown. Note that these are raw results.

9.4.2 District resolution base case results

Figures 9.6 and 9.7 show that most cities have higher indicator scores than their surrounding districts. The districts that form the extended commuter hinterland of larger cities have lower scores. The colour scheme emphasises in red where these districts are. Epping Forest has the lowest district resolution indicator score (raw values). The hilly city of Sheffield and the Pennine districts to the north of it have below average indicator scores. Table 9.3 lists the districts with the highest and lowest base case scores.

Table 9.3 Lowest and highest indicator values by district

Raw results are shown in the table.

Lowest		Highest	
District	**Base-case %**	**District**	**Base-case %**
Epping Forest	30	Isles of Scilly	82
Sevenoaks	31	City of London	77
Tandridge	32	Cambridge	63
Chester-le-Street	32	Westminster	62
Bexley	32	Norwich	61
Bromley	32	Barrow-in-Furness	59
Brentwood	32	Blackpool	58
Castle Point	32	Exeter	58
Havering	33	Oxford	58
North East Derbyshire	33	Kensington and Chelsea	57

9.4.3 Visualising results in different ways.

The rationale for visualising the results in different ways is to ensure that particular zones are not overly emphasised and ensure that results at different scales can be visually compared. These two points contribute to ensuring that the results are not misrepresented.

9.4.3.1 Map and cartogram

Figure 9.7 emphasises the indicator scores in the large more sparsely populated districts. This is because the size of each district on the page is based on the land area covered by the district. This is useful for rural policy analysis, but less so for urban policy analysis (for example it increases the importance of small populations in rural areas over large populations in urban areas). For national and urban policy analysis, a cartogram is more useful (see Figure 9.8). As explained with Figures 9.1 and 9.3, the cartogram gives a clearer impression of the proportion of the population with capacity to commute. It also shows more clearly the district level pattern in the major urban areas. The cartogram confirms the pattern that the indicator is higher in most large urban areas than in the districts which surround them.

Most obvious is London. The districts outside central London show a roughly concentric ring pattern with lower scores towards the edge, which highlights the effect of London's commuting sphere of influence. A smaller example of the same pattern exists around the other conurbations with the exception of South Yorkshire. The pattern is also less pronounced around Leeds as it is only present to the South.

All but two of the ten lowest scoring districts are found in the outer most ring with London at its centre. Long distance commuting to London is well known in research and the media (see for example: Green et al., 1999; Gregor, 2013; Tighe, 2014). Commute distance appears to be a major influence on the district level pattern of resilience to fuel shocks. The hilly districts of the Pennines have scores below 38%, suggesting the influence of topography on the indicator. However with these districts falling in between Manchester, Leeds and Sheffield, commuting may also be an influence. A third factor is that large parts of these districts contain accessible rural areas. The low scores may be linked to findings by Banister and Gallent, (1998); Green and Owen, (2006) summarised in Axisa et al., (2012) that accessible rural areas with proximity to intercity routes encourage longer trips for those who can afford it; as it increases access to the employment centres of large cities. The maps plus a knowledge of the basic geography of England gives a suggestion of which attributes exert greatest influence in a particular area. The next section tests this further.

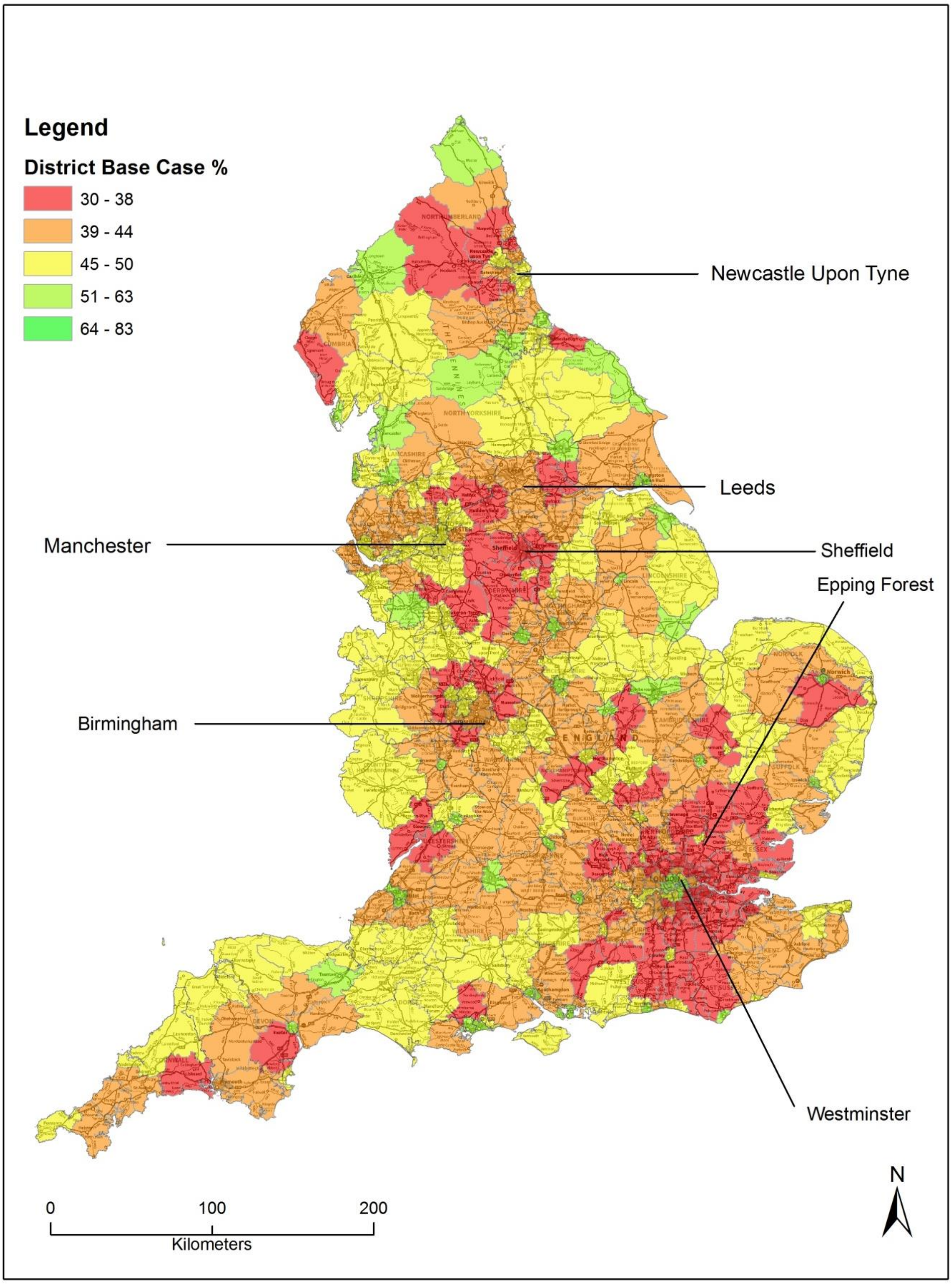


Figure 9.7 Base case indicator value at district resolution.

The values in the five categories are percentages of the number of people in each district who could commute to work by walking and cycling in a traffic network with no motor vehicles.

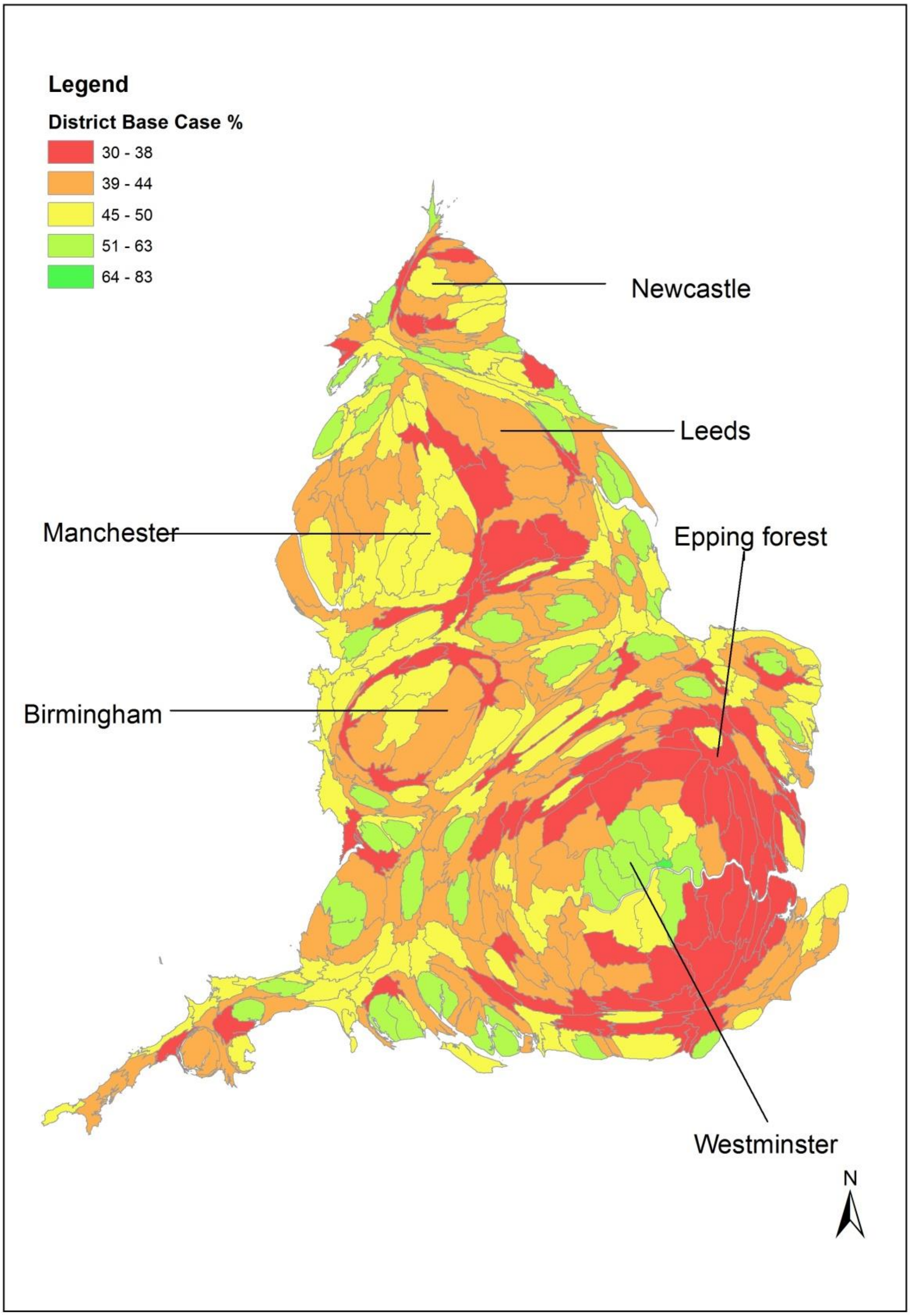


Figure 9.8 Cartogram showing base case indicator result for English districts.

Values are the percentage of the number of people in each district who could commute to work by walking and cycling in a traffic network with no motor vehicles. Districts are resized based upon the number of employed people resident in the district. It emphasises populous urban districts. The Gastner Newmann method (Gastner and Newman, 2004) is implemented using an ARCGIS plugin. (ESRI, 2009).

9.4.4 Identifying the effect of particular attributes on the indicator

The correlation between the indicator and attributes was assessed. The purpose of this test is to establish the strength of association between particular attributes and the indicator value. Proximity to urban centres appears associated with high base case indicator values. Being in areas with commuter settlements and being in hilly areas appears associated with lower base case indicator values. Young adults and those with level 1 qualifications are also associated with higher base case results nationally. Correlations between base case results and the continuous attributes used in the modelling process was calculated (see Table 9.4). The correlations are generally weak though there is some variation. It suggests there is a complex interaction of effects of each attribute on the indicator depending on location.

Even weak associations combined with local knowledge, may help in understanding the complex interactions of the effects of different attributes on the indicator locally. Taking the cases in Table 9.4, Epping Forest has the lowest base case indicator score of any district. The strongest association with the base case indicator is bike availability. It is not a very hilly district. It is also on the edge of London so there are employment centres relatively close by. Strangely, maximum travel distance is associated with a decrease in indicator score. One speculative explanation would be that there is a negative association between fitness and deprivation[46], and a negative correlation between income and commute distance. This suggests a complex interaction between attributes: Fitter people come from more affluent areas, they have higher paying jobs in the centre of London, but the long commutes outweigh the fitness[47].

Calderdale and Sheffield are hilly districts (Calderdale has a mean road gradient of over 5%). If gradient were exerting a large effect on indicator scores, there should be a moderate to strong negative correlation. The correlation with gradient is very low in Calderdale. However, in Calderdale there is little contrast in gradients between the different Output Areas so this

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[46] For example in a study by Stafford et al., 2007 in areas with features indicative of deprivation, physical activity was found to be lower and obesity higher than in less deprived areas

[47] Very few people could not get all the way to central London in an hour by bike (Epping to Westminster is over 30km).

weakens the correlation. The correlation with the percentage of females in the district is somewhat higher than nationally or other areas. This suggests a gender effect should be considered in an explanation of the level of adaptive capacity to fuel shocks in this district.

Table 9.4 Correlation of attributes with base case indicator values

*significant at 0.05 using Pearson's correlation co-efficient.

Attribute	Cambridge	Epping forest	Calderdale	Sheffield	National
working population in district	.036	-.171*	-.266*	-.247*	-.148*
mean maximum travel distance	.419*	-.229*	.143*	.289*	.135*
mean commute distance	-.379*	-.105*	-.272*	-.197*	-.288*
mean Pedal Power	.275*	-.138*	.353*	.340*	.177*
mean BMI	-.114*	.009	-.218*	-.252*	-.145*
mean age	-.188*	.051	-.358*	-.326*	-.229*
mean bike availability	.353*	-.328*	-.256*	.015	-.215*
mean need to escort	-.280*	-.059	-.072	-.114*	-.029*
mean gradient	-.096	.056	-.121*	.301*	-.109*
% female	.011	.005	-.293*	.088*	.042*

In terms of gradient, Sheffield seems anomalous. The indicator score increases with gradient. However Sheffield is a very hilly city (5% average gradient). There are hilly areas close to the city centre. It may be that despite being hilly, many people live close enough to the city centre to access the jobs there. This proximity may override the effect of gradient. In very flat Cambridge, maximum travel distance has a somewhat higher correlation with the base case indicator than nationally. Bike availability is also less weakly correlated than the hilly districts and nationally. Because it is very flat around Cambridge, maximum cycling distances for fit individuals are higher than most other districts. This reduces the effect of commute distance. The non-linear complex relationship between the indicator values and attributes has been shown in this section. This phenomena formed part of the justification for using spatial microsimulation argued in Chapter 5.

9.5 Testing the ability to show the effect of policy at Output Area resolution

The policy case indicator is:

> The capacity of an individual to commute to their current place of work using only walking and cycling given implementation of specific policies in a network with no motorised transport following a fuel shock.

The policy effect is:

> The difference between base and policy case indicator values.

Three separate policies were tested plus a policy package combining the policies[48]:

Health: This policy has three aspects. Firstly, improve the Body Mass Index (BMI) of the population so no individual is obese (BMI >30) secondly ensure all individuals complete the recommended level of exercise (75 minutes of vigorous exercise per week) and thirdly that individuals have a level of fitness with VO_{2max} rated at least "fair" for their age and gender.

Bicycle availability: Ensure all working individuals have access to a bicycle.

"Free Range Kids": Ensure that it is safe and practicable for children aged 7 and over to walk or cycle to school unaccompanied by an adult.

Policy package: The three policies tested above were tested as a combined package.

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[48] Section 4.3.2 discusses the reasons for the policies chosen.

9.5.1 Policy effect test and rationale

There is no stochastic difference between base and policy case results (See discussion in Section 6.5). The test of policy effect is:

$$\text{Policy effect} = |\text{raw policy case} - \text{raw base case}| - \text{error}$$

[9.1]

This is because the raw effect may be smaller than the actual effect (or vice versa). For example, in a particular OA, the Free Range Kids policy may have a raw effect of 3%. However if the sensitivity of the indicator to the effect of escort trips on time budget is acknowledged, the base indicator score in that OA could be +-2.4% different. This affects the size of the policy effect. A spatially explicit indicator should make clear to policy makers the zones where the modelling process can confidently assume that a policy would have a positive effect. For this reason the raw and minimum effects are reported (minimum effect is the raw effect minus the error estimate). The minimum effect is also a conservative estimate of the impact of a policy. Conservative estimates present lower risks of under-performance for policy makers. The results of the test are summarised in Table 9.5.

Table 9.5 Output Areas where the effect size is greater than the error and uncertainty identified in Chapter 8.

Policy	**Mean raw effect in all OAs nationally.**	**Number of OAs where** ***raw effect – error >0***	**% of OAs where** ***raw effect – error >0***
Health	4.7	28954	17.5
Bicycle availability	11.4	129281	78
Free Range Kids	1.8	241	0.1
Summed effect of policies	18.0	160798	97
Policy package	23.1	163927	99

9.5.2 Spatial distribution of policy effect

The spatial effect of the policy package is shown in Figure 9.9. This map takes account of the error and uncertainty identified in Chapter 8. It is interesting to note from the map showing error and uncertainty by Output Area (Figure 8.12), that the OAs with the largest error tend to be found in the same areas as the highest policy effect values. This shows that caution must be exercised when looking at effect size. It is a reason why the raw policy effect has not been presented in the results. However Figure 9.9 demonstrates that size of error and uncertainty is smaller than the policy effect, so it is possible to say with some confidence that the policies tested would have an effect.

The central areas of cities are relatively unaffected by the policy package or other policies. There is an annulus (doughnut shaped ring) less than 5km from city centres. Newcastle is shown as an inset in Figure 9.9. Harrogate, also shown as an inset on the map, does not show such a strong effect. Unlike Newcastle and other cities, Harrogate does not have a complete ring of OAs on the outskirts of the town where the policy package effect is above the national average.

Any information about the local areas helps to contextualise and begin to explain the results. For example, Harrogate has the same pattern as many smaller towns. In small towns, the urban area is small enough that a large proportion of people working within the town are able commute there using active modes. In addition, because Harrogate and towns like it have a dormitory function there will also be many workers who cannot access other urban centres, for example Leeds is a 30km bike ride away. The policy package does appear to have a greater effect on the North side of Harrogate than the South. This may be due to Leeds being to the South encouraging greater levels of commuting. However it could be related to socio-economic and demographic differences. The South side of Harrogate is a particularly affluent area and affluence is associated with longer commutes (DfT, 2011b). The results could be further contextualised if compared to other indicators which map socio-economic and demographic differences. In the next section, the indicator developed in this thesis is examined in conjunction with other indicators.

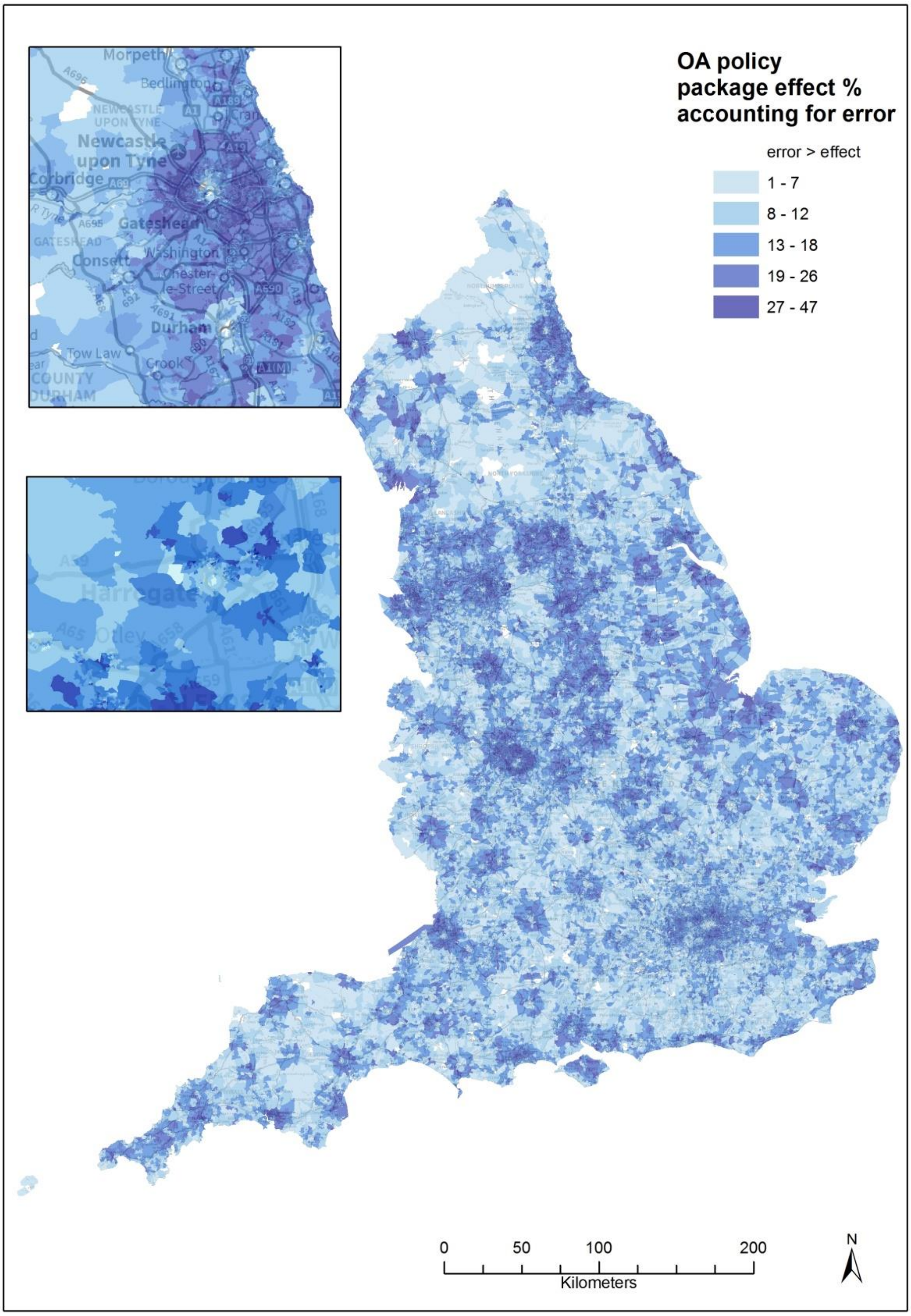

Figure 9.9: The effect of the policy package at OA resolution for the whole of England

This map accounts for error and uncertainty identified in Chapter 8. The insets show Newcastle and surrounds above, and Harrogate below. The policy package has greatest effect in areas surrounding city centres. The distance from the centre where the effects are greatest varies between cities. The legend shows percent raw differences between policy package and base case indicator values.

9.6 Testing the ability of the indicator to relate to wider issues

It is helpful to test the ability of the indicator to relate to wider issues because this is one of the criteria for good indicators discussed in Section 3.3.3.2. The ability of the indicator to do this is demonstrated below by identifying the least resilient areas by linking results with other indicators (the Index of Multiple Deprivation and the Output Area Classification).

9.6.1.1 Contextualising the indicator using the Index of Multiple Deprivation

When the indicator is contextualised in terms of deprivation, it helps to identify the least resilient (or most vulnerable) areas. The reason for this assumption is, that if a person is unable to commute to work after a fuel shock using active modes, then they will have to employ some other strategy in order to adapt or be resilient. A simplifying assumption is that if a person comes from a deprived area, it is likely that they are deprived, and are less likely to have other resources which could help them adapt to a fuel shock. One measure of deprivation is The English Index of Multiple Deprivation. It is measured using a non-compensatory 11 attribute index (McLennan, 2011). The Index of Multiple Deprivation is published at LSOA and district resolution (DCLG, 2012). To contextualise the indicator in terms of deprivation, the correlations between deprivation, and both raw base-case and raw policy-case results were tested (see Table 9.5). It is interesting to note that the policy case indicator has a higher correlation with deprivation than the base case. This suggests that the policies generally have a greater effect in more deprived areas. This suggests the number of least resilient areas should be relatively small.

Table 9.6 Correlation between the Index of Multiple Deprivation and the policy case

The correlations of Index of Multiple Deprivation (IMD) score with the policy case indicator value are in the middle column. The correlations with the effect of the policy package are in the right hand column

	Correlation of IMD score with	
	Indicator value	**Effect on indicator**
Base Case	.371**	-
Policy Package	.553**	.401**
Health	.379**	-.095**
Bike	.528**	.541**
Free Range	.388**	.374**

The least resilient areas were mapped. Least resilient LSOAs were defined as those which are both in the most deprived quintile of the IMD and have a raw policy case indicator value in the lowest quintile nationally (below 59%). 190 least resilient LSOAs were identified. Four areas with high concentrations were identified. East London and surrounds had 74, the former Yorkshire coalfield had 27, the former North East coalfield 24, and South Birmingham 12. These are shown in Figure 9.10 .

Figure 9.10 Least resilient LSOAs

Concentrations were found in the areas above (From top Left; former North East coal field, East London, Selly Oak-Rubery Birmingham, former Yorkshire coalfield. 190 least resilient LSOAs were identified.

9.6.1.2 Contextualising the indicator using the Output Area Classification

The indicator can be further contextualised at Output Area resolution using the Output Area Classification. The Output Area Classification is a geo-demographic segmentation of Output Areas into groups with similar socio-economic characteristics. It uses data from the 2001 UK census (Vickers et al., 2005). There are 7 named super-groups “Blue collar communities”, “City living” , “Countryside”, “Prospering suburbs” , “Constrained by circumstances”, “Typical traits” and “Multi-cultural” (ibid). Output Areas are assigned to these groups based on a statistical analysis of 41 variables reported in the 2001 census (Vickers and Rees, 2007). The names were chosen to attempt to offer some understanding of the character of each Output Area and its population. A further understanding of the nature of the census attributes most common in each type of area is found by looking at the summary Table produced in Vickers and Pritchard, (2010)[49]. The countryside and prospering suburbs groups have more OAs in the lowest base case indicator quintile than the highest. All other super-groups show the opposite trend as shown in Figure 9.11.

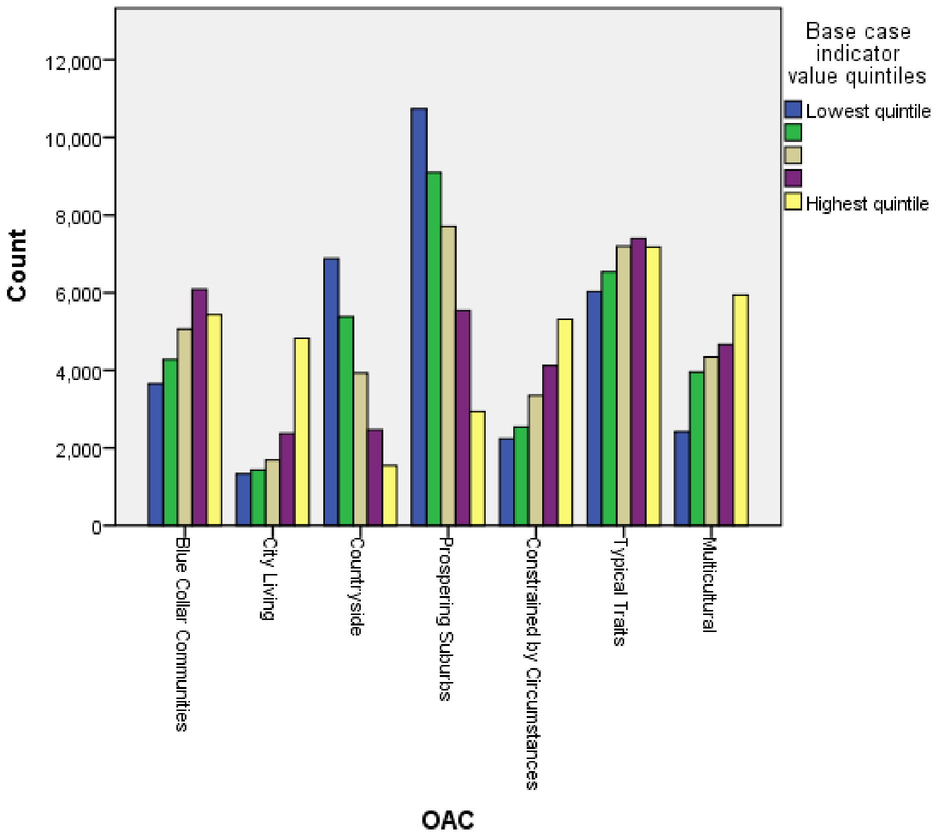

Figure 9.11 Count of Output Areas in each indicator quintile by Output Area Classification (OAC) super-group.

Note raw results are shown

49 A copy is included in appendix 9.1

Examining the spatial pattern, the following observations were made. 15% of Blue Collar Communities are in the lowest quintile of base case indicator scores (the upper bound for the lowest quintile is 33%). Only 8% of Blue Collar Communities are in the lowest quintile for the policy package (<55%). Their distribution is similar to the least resilient LSOAs shown in Figure 9.10. City Living Output Areas in the lowest base case indicator quintile are concentrated in sub-centres of urban areas e.g. Horsforth in North West Leeds. Countryside OAs in the lowest base case indicator quintile appear most concentrated in the rural –urban fringe and inner rural areas. This seems particularly pronounced close to major route ways and rail networks (For example the villages of Panal, Weeton and Huby which are along the Harrogate - Leeds rail line). Prospering suburbs OAs with indicator scores in the lowest base case quintile are found principally on the edges of urban areas as expected.

Typical Traits OAs with low base case indicator scores are found at a similar distance from cities to the Prospering Suburbs OAs. The general pattern is that Typical Traits OAs in larger towns do not fall into the lowest quintile of base case indicator scores. Nationally, the typical traits lowest quintile is found less around the West and East Midlands conurbations than London and the Northern conurbations. The Trans-Pennine commuter corridor appears to have a large proportion of the Typical Traits OAs which fall in the base case indicator lowest quintile. Limited employment opportunities in small Pennine towns and villages may force this segment of the workforce to commute in larger numbers to Leeds and Manchester. This relates to the correlations in Table 9.4. The Constrained by Circumstances OAs in the base case indicator lowest quintile are found in similar areas to the Blue Collar Communities in the lowest quintile and the least resilient LSOAs.

9.7 Local analysis: Case study Leeds.

The previous sections of this chapter have focussed on examining results at a national extent. Results can also be presented at a local extent to understand a specific area in more detail. To do this, a more in depth study of Leeds Local Authority is presented. The factors which influence the indicator are mapped. When presented at a local extent, this aids understanding of which factors have the most powerful influence on the indicator in particular locations. Local analysis has also been used to assess the indicator against other methods of estimating capacity to make journeys by active modes.

9.7.1 Description of individual attributes which contribute to the indicator

In Figure 9.12, showing the distribution of age, there is a concentration of younger people in the centre and immediately to the North West. The former is associated with young professional inhabitants and the latter with students. These population segments are more likely to be physically active and fit; as can be seen by Figures 7.1 to 7.6.

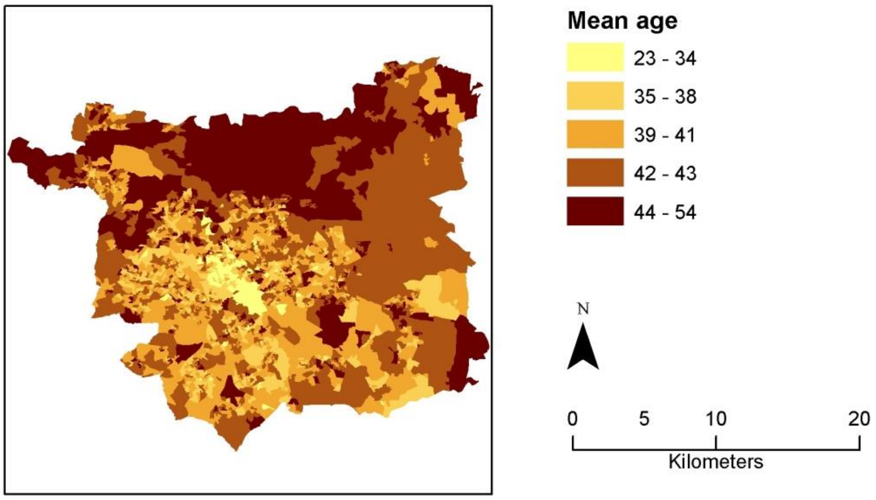

Figure 9.12 Mean age of working population in Leeds OAs

Figure 9.13 shows a concentration of OAs in the city centre which have a smaller proportion of female working residents. There is also a concentration of OAs in the far North East in the town of Wetherby, which have a smaller proportion of female working residents. The large areas approximately 7km North and North East of the centre are sparsely populated OAs. The error in the spatial microsimulation for age, gender and economic activity is low (see Section 8.2) suggesting the pattern is valid.

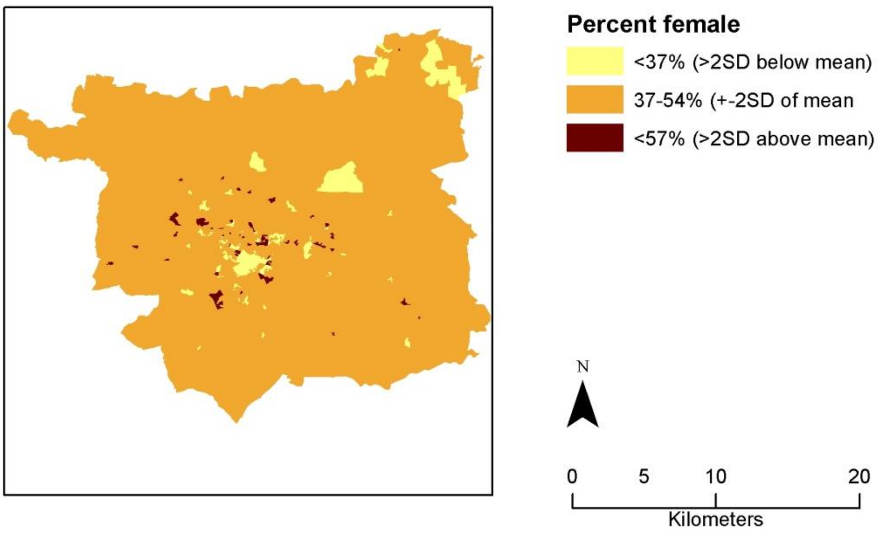

Figure 9.13 Percentage of females in the working population in Leeds OAs

Figures 9.14 and 9.15 show there is a concentration of OAs with lower mean BMI values and lower rates of obesity in the centre and immediately to the North West. There is also a concentration of younger workers in these areas. BMI generally increases with age so these maps appear to be broadly consistent with Figure 9.12.

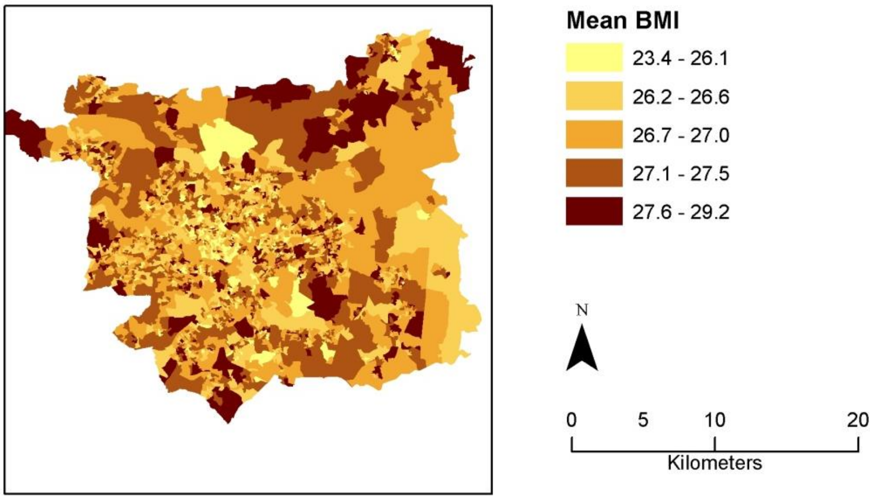

Figure 9.14 Mean Body Mass Index (BMI) of working population in Leeds OAs

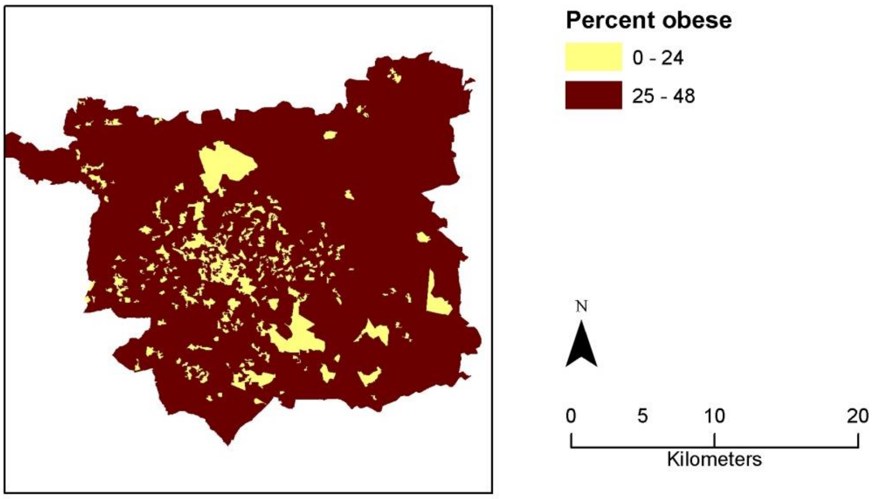

Figure 9.15 Percentage of the working population classed as obese grouped by OAs with obesity rate above or below national average of 24%.

The mean pedalling power for all Output Areas is 78 Watts though there is considerable variation (minimum 36, maximum 124). There is a concentration of the highest values in the centre and immediately to the North West. The former is associated with young professional inhabitants and the latter with students (though students are not classed as working individuals). These population segments are more likely to be physically active and fit; as can be seen by Figures 7.1 and 7.5. The lowest values appear at the edge of the city. This pattern is similar to those of age, percentage of females, BMI and obesity. This is as would be expected because Pedalling Power is determined by these attributes in the modelling process.

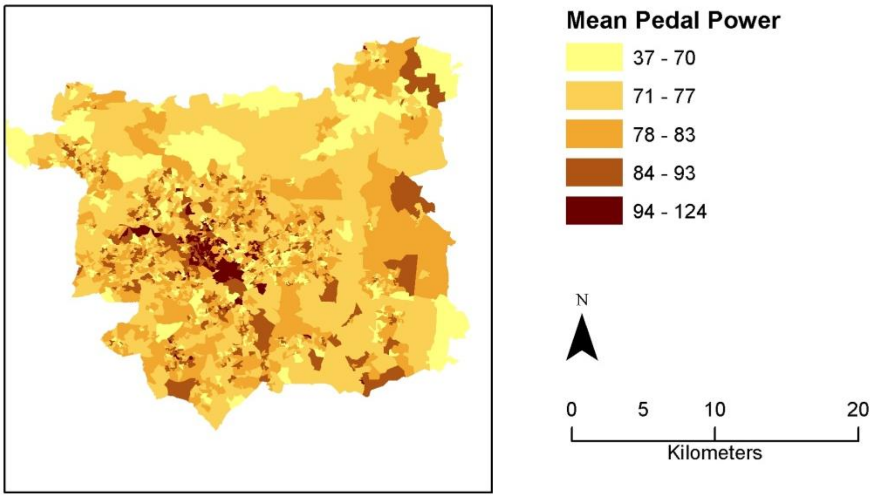

Figure 9.16 Mean Pedal Power of working population by Leeds OAs

Figure 9.17 shows that rates of bike availability are particularly low in the suburban annulus where policy effect is greatest (see Figure 9.9). Bike availability appears high in the city centre. This may be explained by the dominance of young male workers who are more likely to have bikes than some other population segments. The city centre is gentrified containing large numbers of young professionals. This is consistent with the modelling process which estimates bicycle availability as being higher in areas where socio-economic status is higher. Bike availability is also higher in the more affluent North of the city than the less affluent South of the city. This is also showing the effect of the socio-economic element of estimating bike availability explained in Section 7.4.4.1.

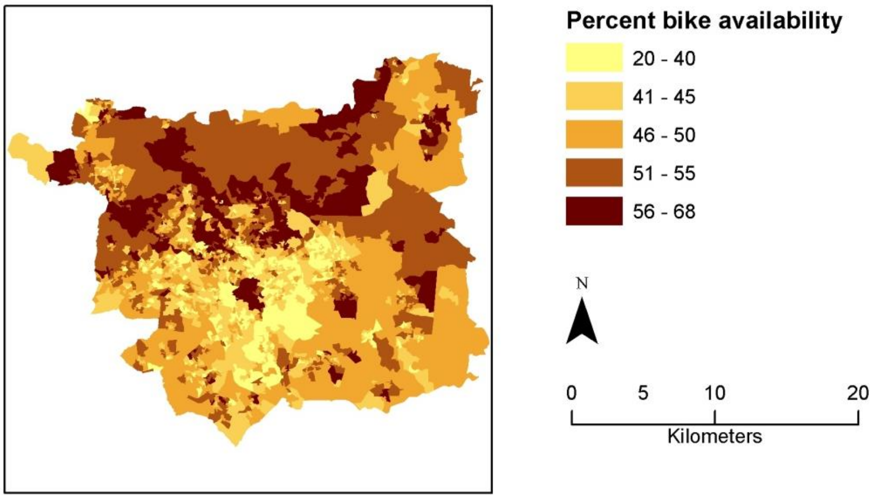

Figure 9.17 Percentage of working population with access to a bike in Leeds OAs

Figure 9.18 shows that in the wedge leading North West from the city centre through the student dominated area of the city there are a low proportion of working individuals who have to make escort trips whilst commuting.

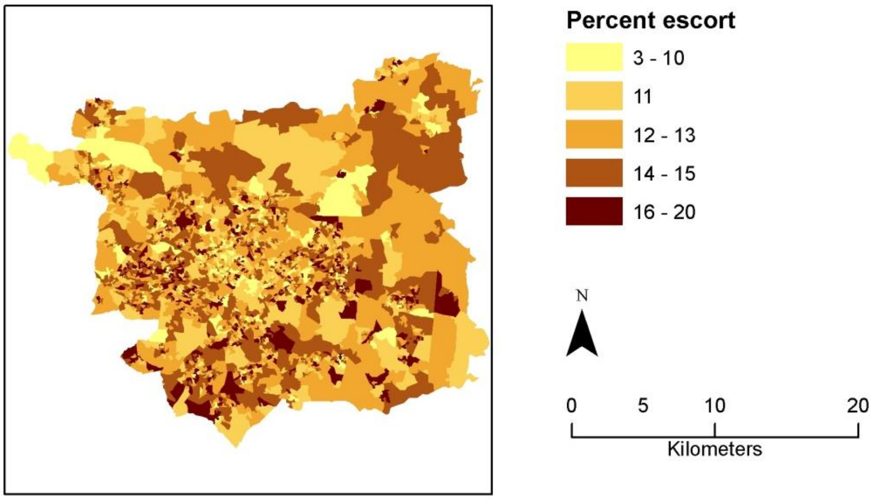

Figure 9.18 Percentage of working population estimated as having to escort children to school as part of a commute in Leeds OAs

Figure 9.19 shows that gradient increases from South East to North West. Though the base case indicator value is generally low in the hilly North West of the city it is also low in the flatter East and South East. The flat areas though contain motorways. Easy access to motorways increases commute distance which also reduces the base case indicator. The rather arbitrary looking straight lines are an artefact of using a 5km x 5km raster grid as the base for the average gradient of roads in an area (this was explained in Section 7.4.5).

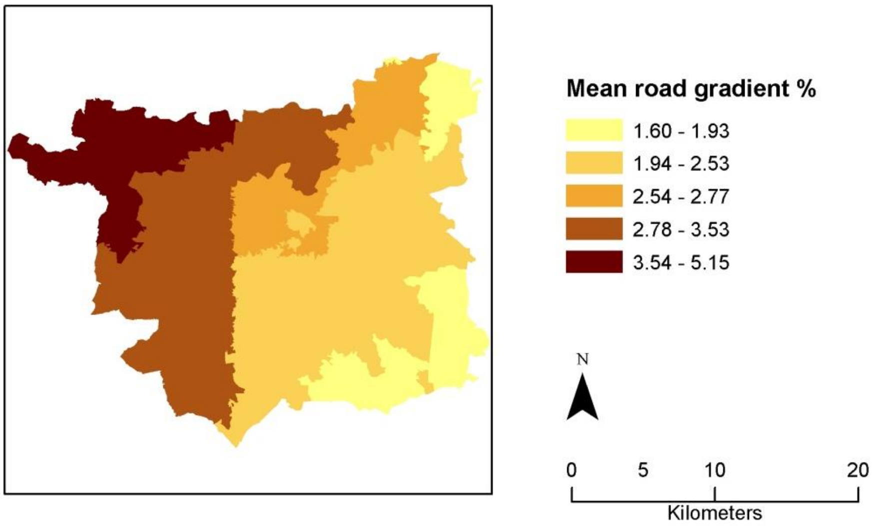

Figure 9.19 Mean gradient of roads in the 5km x 5km cell in which the OA centroid falls

See Section 7.4.5 for further details

Comparing the base case indicator map of Leeds (Figure 9.20) with the maps of individual attributes (Figures 9.12-9.19) it is possible to visually identify that age, Pedal Power and bicycle availability clearly have an impact on the indicator. The influence of the other attributes is more subtle. The correlations between base case indicator and the attributes mapped in Figures 9.12-9.19 are shown in Figure 9.21.

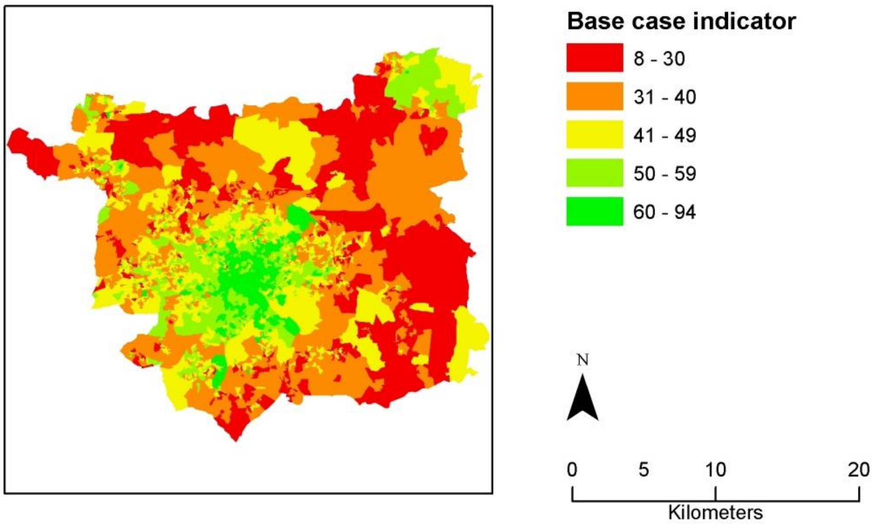

Figure 9.20 Base case indicator Leeds OAs

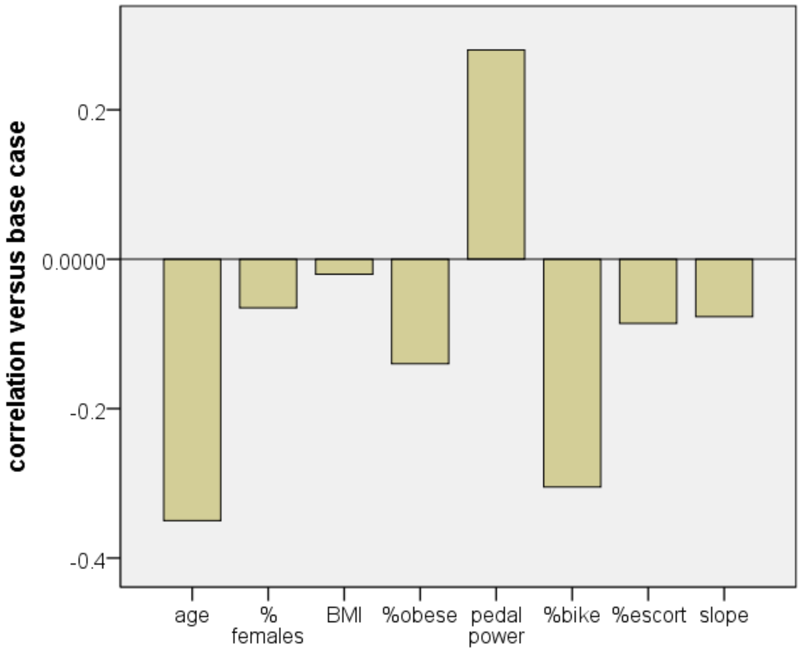

Figure 9.21 Correlations of individual attributes with base case indicator in Leeds OAs

9.7.2 Assessing the improvement in estimation of capacity to walk and cycle over existing methods.

This section compares the indicator to three existing methods of estimating capacity to make journeys by active modes: Assuming everyone can cycle 8km; ignoring constraints on bike availability and the need for escort trips and an all or nothing estimate of capacity.

9.7.2.1 Assuming everyone can cycle 8km

Assuming all people can cycle 5miles / 8km is common in transport planning as explained in Section 3.2.1. Typically a buffer is drawn on a map to indicate the region supposedly accessible by bike. It is a poor estimate of capacity to commute by walking and cycling. It fails to account for variation in individual physical attributes, bicycle availability and constraints such as needing to escort children as part of a commute. If instead of calculating maximum distance based on the methods explained in Chapters 6 and 7, the simple assumption is made that all people can travel 8km, the mean difference in indicator value is 26%. Figure 9.22 maps the differences. The greatest differences (34-54%) are found in the annulus of greatest policy effect which can be seen by comparing Figure 9.22 with Figure 9.9. This suggests the methods used in this thesis produce a significant improvement in estimation of capacity to make journeys by walking and cycling compared to using simple buffers.

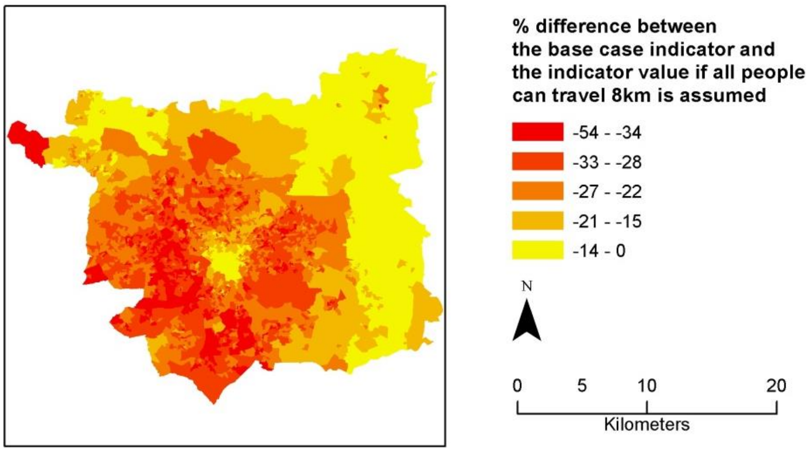

Figure 9.22 Percentage difference between the base case indicator and an alternative version of the indicator which assumes all people can cycle 8km.

9.7.2.2 Assuming no constraints on bike availability and the need for escort trips

Figure 9.23 shows mean maximum distance for each OA used in the base case indicator calculation. There is a concentration of higher values in the city centre and immediately to the North West. The former is associated with young professional inhabitants and the latter with students (though students are not part of the working population). These population segments are more likely to be physically active and fit; as can be seen by Figures 7.1 to 7.5. This is also consistent with Figures 9.12-9.15.

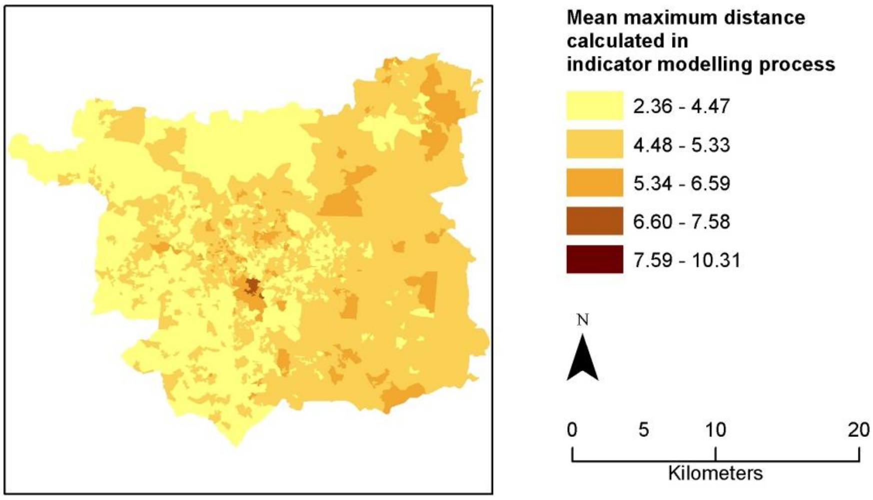

Figure 9.23 OA Mean maximum distance used in the base case indicator calculation

Figure 9.24 shows the estimate of mean maximum distance is greater if the constraints of bike availability and the need to escort children are ignored. The influence of gradient is evident in both 9.23 and 9.24; maximum distance increase the flatter South East and East.

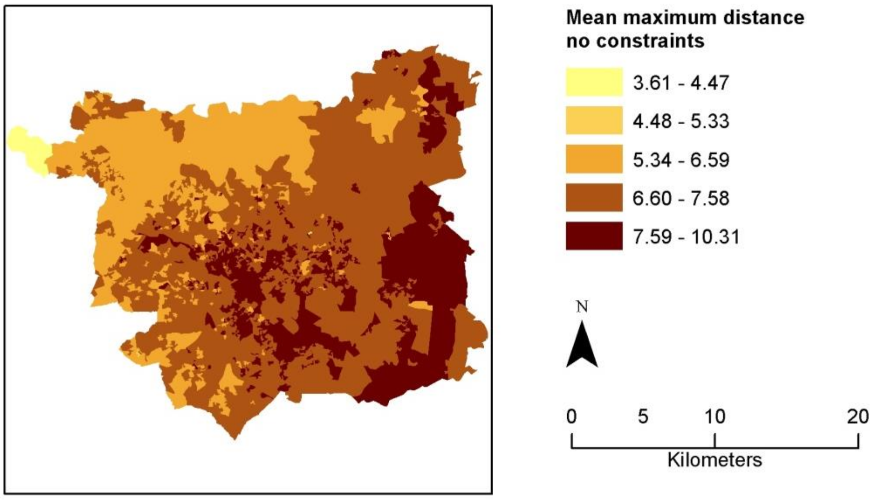

Figure 9.24 OA Mean maximum distance assuming no constraints of bike availability or escort journeys

Figure 9.25 compares the difference between 9.23 and 9.24. The difference in maximum distance is striking. The difference in maximum distance is least in the North. It is generally highest in the annulus of greatest policy effect (see Figure 9.9). This suggests the indicator is more able to identify areas which can benefit from the tested policies than a model which ignores constraints on mobility. Mean difference between an unconstrained maximum distance and the indicator method used in this thesis is 2.64km. Ignoring these constraints produces a mean 73% over estimate of maximum distance. These maps further demonstrate the importance of considering constraints on people's mobility when estimating capacity to travel.

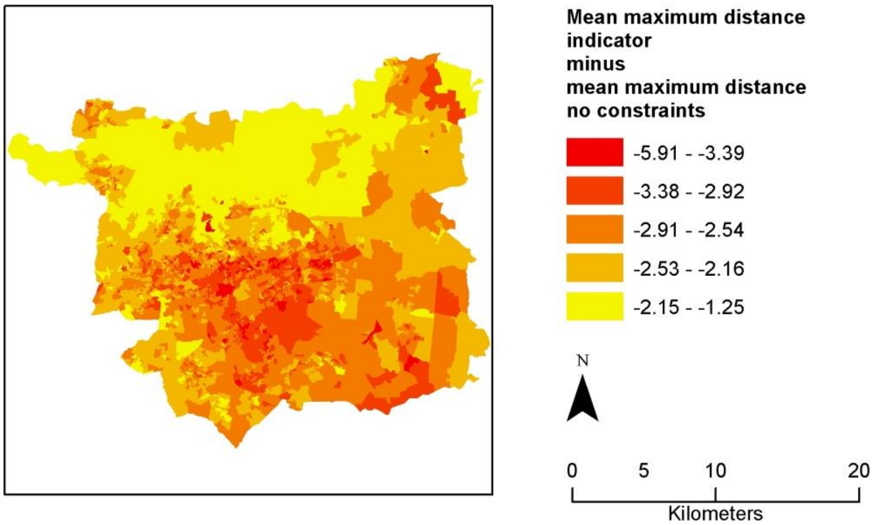

Figure 9.25 Comparing calculations of mean maximum distance in Leeds OAs.

9.7.2.3 Assuming an all or nothing estimate of capacity

Figure 9.26 is an example based on the simple model introduced in Table 5.1. It is an over simplification showing areas where the mean maximum travel distance is greater than the mean commute distance. The OAs where mean travel distance is higher than mean commute distance are found in inner city areas. These areas do not seem concentrated in gentrified areas of the inner city. These areas are generally where there is a high proportion of households of South Asian origin. This may be a pattern of an enclave (Ritzer, 2007) related to either ethnic / cultural or socio-economic factors.

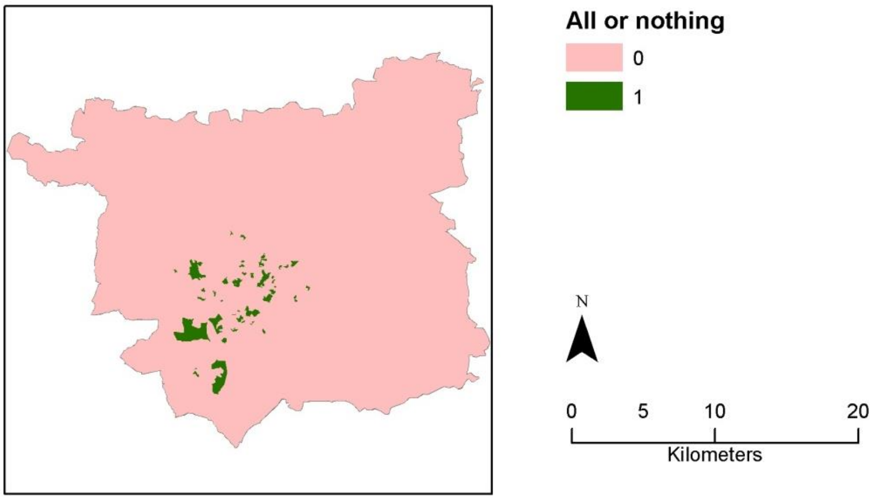

Figure 9.26 OAs where mean maximum travel distance by walking and cycling exceeds mean commute distance

9.7.2.4 Conclusions of local level analysis: Leeds

The spatial patterns of attributes which influence the indicator are identified. They are consistent with each other and with local knowledge. Different attributes appear to exert different levels of influence in different areas. This is a point which geographers would expect, but the value of mapping this data is that it aids understanding of the effect of geography on the indicator. It again bears out the assertion that spatially explicit policy measures add understanding and therefore value.

Assuming everyone can cycle 8km (a common assumption in transport planning discussed in section 4.3.1) overestimates capacity of the population to commute by active modes. The indicator identified a mean difference of 26% across all OAs. By considering constraints the indicator estimates of maximum distance differ by 73% compared to methods which ignore constraints. These differences suggest the indicator calculation methodology has produced significant improvements in the estimation of capacity to travel by active modes.

9.8 Discussion

In addition to achieving objective 4, there are several other outcomes from Chapter 9, which are grouped into three sub-sections below.

9.8.1 Flexibility and ease of use

The results have been presented at multiple resolutions, with multiple scales, as maps and cartograms as well as graphs and tables. The range of outputs improves the quality of the indicator in terms of ease of use and flexibility. Outputs can be produced, tailored to the needs of the decisions being considered (i.e. local or national level planning decisions). The base case indicator results are presented at several resolutions. The effect of small settlements, anomalies and the heterogeneity within districts is shown at these fine resolutions.

At each resolution it is possible to give practitioners and policy makers an overview at a national extent and a more detailed view at a local extent. The indicator is a tool which is responsive to different needs. It can provide national level policy makers a means of comparison between districts, but it also allows local planners to identify the specific Output Areas most likely to have low indicator scores or be most positively affected by a policy.

Multi-resolution mapping easily conveys the idea of heterogeneity within districts, and helps move policy makers away from the ecological fallacy based "one size fits all" approach. As discussed in Sections 1.4 and 4.1.1.2, The development of spatially explicit modelling tools generates advances in the effectiveness of transport and social policy (Ballas et al., 2005b; Openshaw, 1995).

Multi-resolution presentation of results increases ease of use in terms of being able to set more appropriate targets. For example a town council may lobby for funds to increase resilience to fuel shocks; arguing they are in a district with a low indicator score. However by examining the fine resolution results it can be seen that the town itself has a high indicator score, but the rural OAs surrounding it have a low indicator score. If an authority is to be given a target to increase the indicator score then specifying the resolution and exact location increases clarity and reduces corruptibility. Reducing corruptibility is discussed further below.

9.8.2 Mapping to reduce corruptibility

Corruptibility is the extent to which indicator results can be manipulated to present a particular point of view (Marsden et al., 2006). Manipulating scale, extent or colour scheme are ways to “lie with maps” (Monmonier and de Blij, 1996) and thus manipulate the indicator. Multi-resolution mapping helps to reduce this problem as does presenting results in other formats such as cartograms and summary data tables.

Cartograms used in conjunction with maps, increase the clarity of the results and help to reduce corruptibility. The cartograms emphasise the size of the working population. Epping Forest for example has a small working population compared to Leeds (56586 vs 307205). Both districts cover a similar area. Increasing Leeds in size on the page proportional to its employed population is indicative of the fact that; in a fuel shock more people in Leeds district would be unable to commute to work than from Epping Forest district. This aids clarity of data presentation and helps planners make informed decisions about whether they wish to prioritise districts with the lowest indicator score or those where the largest number of individuals would be affected.

Map colour schemes are generally designed to show similar areas in the same colour. The Jenks Natural Breaks method (see its implementation in the ArcGIS software in ESRI, 2012) of delimiting categories in choropleth maps is generally seen as good practice (Monmonier and de Blij, 1996). This has been done with the district resolution maps above (Figures 9.7 and 9.8). However comparing maps at different resolutions is more difficult because the range of values is different and the ‘natural breaks’ fall at different points. For this reason District maps have been reproduced in appendix 9.2. Defined interval (e.g. breaks at 10, 20, 30% etc) is used so that map colour is consistent between OA and district maps. To reduce the problem of arbitrary boundaries between classes, a larger number of classes is used (10 in the defined interval versus 5 in the natural breaks maps). Though this may seem cumbersome and almost repetitive it serves as another means of reducing the “corruptibility” of the indicator. It shows that similar patterns can be discerned in using different legends suggesting that the data is not being misrepresented (Monmonier and de Blij, 1996).

9.8.3 Policy implications

A range of analysis has been carried out in this chapter. The policy relevant findings of these results are:

- Only 44% (±4.85[50]%) of working people in England have the capacity to get to work by walking and cycling.
- The indicator value is affected by a complex interaction between individual attributes and location.
- The pattern of adaptive capacity to fuel shocks is heterogeneous within districts.
- A combination of increasing bicycle availability, increasing physical activity reducing obesity and making it safe for children to get to school unaccompanied ("Free Range Kids"[51]) has a positive effect in 99% of Output Areas.
- The effect of these policies is generally greater in more deprived areas.

The implication of the results for policy makers is that it is possible to identify vulnerability to fuel shocks and the effects of the policy package tested in this research at a fine spatial resolution. This means that it would be possible to appraise the benefits of acting to increase resilience to fuel shocks using current transport planning frameworks.

The implications of the scope and approach for policy are as follows: An indicator considering fuel shocks broadens the policy debate by allowing discussion of a broader range of options than if a limited by current patterns of high fuel availability and dependence (Banister and Hickman, 2013). Contextualising the indicator in terms of deprivation and the Output Area Classification shows ways to gain further understandings of constraints on capacity to adapt (which could be investigated in future work). Focus on capacity sets an upper bound on the range of possible behavioural responses following a fuel shock. Should a fuel shock occur it is hypothesised that the initial adaptive capacity estimated in this thesis would impact upon initial behavioural response to the shock. Initial adaptive capacity and behaviour would in turn affect capacity, behavioural response and resilience outcomes in the medium and longer term. A separate predictive model would be required to attempt to predict the exact number and type of journeys people would choose to or be forced to make, accounting for their attitudes and behaviours resulting from the changed societal context. This would require speculation. A key feature of this thesis has been to avoid wherever possible speculation about human behaviour. This has been key to ensuring policy relevance; the avoidance of speculation has contributed to an indicator which is measureable, and non-

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[50] For details of how this margin of error was estimated see Section 8.5

[51] "Free-Range Kids" is a campaign run by Sustrans in 2013 to make walking and cycling the norm for local journeys, particularly the journey to school. http://www.sustrans.org.uk/blog/calling-government-create-child-friendly-communities

corruptible which are criteria for good indicators (Marsden et al., 2006). Meeting good indicator criteria provides an argument that this indicator should be introduced into multi-objective strategic transport planning as per the aim of this thesis.

10 Conclusions and further work

This Chapter begins with a summary of findings in Section 10.1. Following that the original contributions of the thesis are reviewed in Section 10.2. The potential for policy impact is summarised in Section 10.3. A review of problems and limitations identified during the research is given in Section 10.4 and areas for further work are discussed in Section 10.5.

10.1 Summary of findings: Assessment of progress towards a good indicator

The key practical feature of this research has been the development of an indicator which is of practical use to transport planners and practitioners. Progress in this direction contributes towards the aim of the thesis. (The aim of the thesis was to estimate the potential for walking and cycling to enhance resilience to fuel shocks and introduce it as a factor into multi-objective strategic transport planning). Demonstrating progress requires demonstrating the quality of the indicator. A good indicator was defined in Section 3.3.3.2 using the criteria devised by Marsden et al., (2006). Table 10.1 summarises the progress made towards these criteria.

Table 10.1 Progress towards a good indicator

Criteria for good indicators	**Steps towards fulfilling criteria**
1. Usefulness	The Indicator can have “Rational – positivist” functions: This has been shown in the Chapters 8 and 9 (validation and analysis of results). As the indicator is not currently measured or used it also has Discursive – constructivist” functions. Trial use with stakeholders would further refine the functions. The indicator can measure the base case and policy case adaptive capacity to fuel shocks. The issue of resilience to transport fuel shocks is a specific example of the generic issue of resource scarcity threatening sustainable development.
2. Clarity	The scope (Section 4.2) and the simplifying assumptions made (see Table 4.2 and 7.5.1) are made clear in the text and as summaries. The influence diagram (Figure 4.3), equations in Chapters 5 through 8, and the description in those Chapters give a detailed account of the indicator construction. This makes the indicator design clear to experts. To make the indicator construction clearer to non-specialists, summary diagrams and tables of the indicator construction have been provided. The maps and data visualisations used in Chapter 9 give clearly understandable illustrations of results to specialists and non-specialists alike.
3.Non-corruptibility	The attempt to clearly explain the construction of the indicator summarised in point 2 is the first step towards non-corruptibility. The validation and sensitivity tests in Chapter 8 make clear the level of error and uncertainty within the modelling process as summarised in Table 8.13. Presentation of results in Chapter 9 demonstrated steps to reduce corruptibility in terms of display of data and by explicitly considering error and uncertainty in the analysis.
4. Controllability	The indicator was shown to be able to relate to wider

	issues in Section 9.5. The indicator can be contextualised in terms of other indicators such as the Index of Multiple Deprivation (IMD) and the Output Area Classification (OAC). The indicator has shown an ability to help analyse the potential for people to participate in activities under different conditions. This is in line with an emerging research agenda to consider the resilience of transport systems in a broader context (for example Marsden et al., 2014 discussed in Sections 2.3.3.4 and 3.1.2 of this thesis).
5. Measurability	A quantifiable indicator of adaptive capacity is produced. Speculative assumptions are avoided as much as possible. Relationships between factors rely on established relationships evidenced in literature. Though simplifications have had to be made, they are made clear (see point 2) – this is an aspect of measurability. Estimates of error and uncertainty are made clear, in Chapters 8 and 9 giving a clear description of the level of precision – another aspect of measurability. This is the first iteration of this indicator so there are limitations (summarised in Section 10.4 below). A further iteration may be able to relax some of the simplifying assumptions, improve the modelling process or gain access to better data sources. These steps would improve measurability. However the measurements made by this iteration of the indicator are fit for purpose within the scope of the indicator defined in Section 4.2.
6. Responsivity / comparability	Chapter 9 shows that the indicator is comparable: Spatial variation can be observed, as can variation between base case and policy case results. The modelling process could produce results that are responsive to changes over time. As new data becomes available such as the 2011 census, it will be possible to estimate changes in adaptive capacity to fuel shocks over time. This would allow the indicator to be used to assess progress towards targets over time – a key feature of evaluating transport policies and strategies (as shown in

	Section 3.2). The current modelling process is static – it produces results at snapshot points in time. In its current state it is not capable of dynamic estimations estimating changes continuously through time.
7. Understandability	The indicator is intended to be straightforward: It can be understood by non-specialists: "Who could get to work by walking and cycling if there was a fuel shock tomorrow" Figures 4.2 and 4.3 go some way to making the factors modelled understandable to a non-specialist. However this could be made clearer. The functional relationships between variables and the data sources do require more explanation and may be difficult to convey to non-specialists. Trial use with stakeholders would help determine how understandable the indicator is.
8. Cost effectiveness	This first iteration indicator uses existing nationwide secondary data sets. There has been no need for expenditure on data or primary data collection during this thesis. If the indicator were developed further by collecting new primary data, the cost effectiveness would depend upon the improvement in precision that it offered.

10.2 Contributions of the work

The aim of the thesis was to estimate the potential for walking and cycling to enhance resilience to fuel shocks and introduce it as a factor into multi-objective strategic transport planning. This aim was achieved by meeting the 4 objectives which were introduced in Section 1.3:

1. To develop a generic approach to estimating indicators of resilience to transport fuel shocks.
2. To develop a static spatial microsimulation based method of implementing, for large populations, a model of capacity to make journeys using only walking and cycling which can be used to generate indicator results.
3. Test the applicability of the design and methods to real data. This will be achieved by integrating a range of secondary data sources from England to report

results at both fine and coarser geographies (Output Areas[52] and coarser geographies in the UK hierarchy).

4. Test the ability of the indicator to show variation between areas in both a base case and when specific policy measures are applied, and consequently report the effectiveness of the tested policies at increasing the resilience to fuel shocks by promoting adaptive capacity by walking and cycling.

By achieving each objective, original contributions were made. The conceptual design of the indicator developed a generic approach to estimating indicators of resilience to transport fuel shocks. This design was original. The novel elements were; that it used the evolutionary conceptualisation of resilience, in combination with an indicator design which is of practical use to planners and practitioners wanting to reflect the positive impacts of sustainable transport policies and sustainable modes (walking and cycling) on resilience.

The conceptual approach of the research is in line with emerging research agendas. These encourage a broader view of resilience in transport studies encompassing not only engineering components but also the ability of people to carry out activities in the broader mobility system (for example Marsden et al., 2014 discussed in Sections 2.3.3.4 and 3.1.2 of this thesis). The significance of the conceptual approach is that as an early example of research in an emerging area, this work will be of benefit to others entering the research area of mobility systems driven approaches to resilience in transport.

The indicator design made practical contributions. The possibility of fuel shocks was established in Chapter 2, because of this, the measure of resilience to fuel shocks is a useful input to any form of anticipatory planning. The indicator design is currently not measured or included in indicators of the benefits of walking and cycling used by policy makers. This is at least in part because there are problems considering it in policy due to a lack of satisfactory indicators. The indicator designed in this thesis begins to address this problem. Specifically, the indicator design helps to fill this gap by being sensitive to a variety of policy measures affecting fitness, obesity, bicycle availability and bicycle infrastructure, whose impacts (at least in the short term) are on a smaller scale than large-scale land use and urban

[52] Output areas are the smallest spatial units used for dissemination of aggregate UK census data. Further information is given in Chapter 7.

morphology change[53]. The justification for using the indicator design as a ‘real world’ policy indicator rather than just as a theoretical scientific model is that the measurement of adaptive capacity is grounded in current data and avoids as far as possible the need for speculation about the future.

Methodological contributions were made in achieving objective 2: A novel hybrid static spatial microsimulation technique was developed and applied: This technique is novel because it attempts to make best use of both Simulated Annealing and Synthetic Reconstruction techniques. It was developed because the indicator required a synthetic population at the finest resolutions (e.g. UK Output Areas); to which Simulated Annealing is suited. It also requires attributes which cannot be found in a single micro-data sample and geographically dependent attributes; to which Synthetic Reconstruction is suited. It applies developments made by the research community who have developed spatial microsimulation techniques, validation protocols and applications to demonstrate spatial microsimulation methods are an appropriate means of geographically explicit modelling for policy (Tanton and Edwards, 2013a). The methodology also built on the assertion that individual characteristics and attributes, particularly those pertaining to capacity for physical effort (Parkin, 2008; Parkin and Rotheram, 2010) lead to more appropriate modelling of walking and cycling in transport modelling and planning. Sensitivity and validation testing of the methods and data described in Chapter 8 show the methods are suitable and that the data used was fit for purpose.

The contribution made by objective 3 was a new means of utilising secondary data sources from the UK. The indicator method was applied to a large case study. The indicator was calculated for the 21million working inhabitants of the 165665 English Output Areas in the 2001 UK census. The case study used the UK census, the Health Survey for England and other secondary data sets. Using existing data has advantages: Firstly, it suggests low costs to implement the indicator. Secondly, using existing national statistical data leads to a model built upon robust validated data and applying new techniques adds value to that data. Thirdly, using existing data sources, which may have already been applied to public policy, creates the potential for integration of data collection and building of better indicator packages.

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[53] Small scale changes may be more effectively targeted at specific people, communities or places, bringing benefits in terms of cost effectiveness and social impact.

The results presented in Chapter 9 showed it was possible to discern the variation in base case indicator values between small zones and also assess the effects of policy on those small zones. Furthermore, the results have demonstrated the flexibility and ease of use of the indicator. The indicator illustrates resilience and the benefits of walking and cycling at both a fine spatial resolution and a wide spatial extent. The extent of the results can also be altered for national and local level planning. Local analysis also showed that the indicator methodology is an improvement on existing means to estimate capacity to travel by walking and cycling. Chapter 9 demonstrated that a wide range of maps, graphs and summary tables can be produced to support planners and policy makers. The contribution made by the results and achieving objective 4 is an increase in the number of spatially explicit transport policy modelling tools. As noted in Chapter 1, the development of spatially explicit modelling tools generates advances in the effectiveness of transport and social policy (Ballas et al., 2005b; Openshaw, 1995).

10.3 Potential for policy impact

In addition to the original research contributions, the results of the thesis have potential for wider policy impact. The policy implications are listed in Section 9.6.3 and reiterated here. The policy relevant findings of these results are:

- Only 44% (+-4.85%) of working people in England have the capacity to get to work by walking and cycling.
- The indicator value is affected by a complex interaction between individual attributes and location.
- The pattern of adaptive capacity to fuel shocks is heterogeneous within districts.
- A combination of increasing bicycle availability, increasing physical activity reducing obesity and making it safe for children to get to school unaccompanied ("Free Range Kids"[54]) has a positive effect in 99% of Output Areas.
- The effect of these policies is generally greater in more deprived areas.

The implication of the results for policy makers is that it is possible to identify resilience (or vulnerability) to fuel shocks and the effects of the policy package tested in this research at a fine spatial resolution. This means that if the current transport planning framework used this indicator, it would be

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[54] "Free-Range Kids" is a campaign run by Sustrans in 2013 to make walking and cycling the norm for local journeys, particularly the journey to school. http://www.sustrans.org.uk/blog/calling-government-create-child-friendly-communities

possible to appraise the benefits of acting to increase resilience to fuel shocks.

Even if the indicator is not used directly in the appraisal process it can have an impact on the transport planning debate (It has a discursive function – indicator functions were explained in Section 3.2.3.1). The indicator may be used by organisations such as Sustrans who wish to demonstrate the vulnerability to transport fuel shocks in particular places and that sustainable small scale policies such as those tested in Chapter 9 could have a positive effect on adaptive capacity and resilience to fuel shocks.

10.4 Problems and limitations

A number of problems were identified in Chapter 7 relating to data availability. The model is based on the assumption that only origin data is available. This limits consideration of factors such as the time cost of making escort trips. Without destination data, it is not possible to determine the extra distance in the trip chain home-school-work versus the non chained journey home-work. The model was constructed as an individual level model rather than a household level model. Modelling unconnected individuals required simplifying assumptions. The probability of escorting a child was based solely on age and gender of the individual and not on household circumstances.

The issues of data availability included the fact that when the constraint tables were built the 2011 census data was not available so the 2001 census was used. The 2001 census is quite out of date. Whilst accepting this as a limitation however, the 2001 data illustrates the application of the method. Additionally it would be relevant to compare changes between the 2001 results and results using 2011 data.

The size of the sample in the Health Survey for England with a measured VO_{2max} was too small to be used on its own. To deal with this issue a regression model was found which could be used to estimate VO_{2max} based on attributes measured for a much larger proportion of the sample. This process was discussed in Section 7.4.2. Whilst this increased the size of the useable sample, further increasing the size of the sample population may be helpful, particularly if the enlarged sample includes individuals with combinations of constraints not represented in the 2008 HSE data. As discussed in Chapter 7 the NSSEC constraint when used with all its categories meant that there were a number of constraint combinations with no representatives in the sample population. The sample population was based on ~11000 records in the Health Survey for England. The most obvious means of dealing with this issue would be to consider using HSE data over several years (for example as Edwards and Clarke, 2009 did).

The lack of data giving a breakdown of the types of bikes available to people based on demographic and socio-economic factors was identified as a data limitation. In the present indicator this factor was excluded. It is possible that the data may be available by accessing commercial data sets, but some knowledge of the composition of the national bike fleet in the public domain would be useful to a future iteration of the indicator.

Not all of the attribute data was available in a single micro-data survey. This meant that two stages of spatial microsimulation were required. The limitation caused by this is that Monte-Carlo sampling had to be used. This resulted in the introduction of stochastic variation, which increased the error in the modelling process. It was a limitation, though the flexibility of the modelling process is seen as an advantage in some ways – it allows the modelling process to be applied in different countries where data availability varies.

The simplifying assumption of the value for circuity being 1.4 is based on the work of others. Work such as that by Levinson and El-Geneidy, (2009) shows that based on their case studies of US cities, circuity varies with journey distance. It is clear from casual observation, that there is some variation in circuity on the UK route network, so better data on this would constitute an improvement to the indicator.

Assumptions had to be made about the slope profile of commuters' routes (i.e. do they travel uphill all the way to work and downhill all the way back or a mixture of up and down on each leg). Given the same gradient, a route which is uphill all the way takes longer than one which has equal shares of up and down. Without knowledge of the exact route of each individual, simplifying assumptions about slope profile cannot be removed.

The testing carried out in Chapter 8 showed that if some of the data issues could be resolved, then it would reduce the level of error and uncertainty in the modelling process. It should also be acknowledged that because of the wide range of data sets being used and the processing required of each, some attributes such as wind speed were dealt with in a more rudimentary way than others. Shortcomings such as this may be better addressed by a further iteration of the model. Chapter 8 identified errors and uncertainty within the modelling process and this represents a limitation on the precision of the modelling process and resulting indicator.

The indicator in its current form also has limits in its scope. Firstly it is only currently considering employed adults in the population and the journey to work. The modelling process certainly shows potential to assess capacity to make other types of journeys, though before implementing these measures there will need to be consideration of the data required to estimate the journey distances to other activities and destinations.

The spatial microsimulation process is based on individuals. As explained in Chapter 5 spatial microsimulation models can also be built at a household level. If this were done it may allow the model to consider further constraints on travel linked to household commitments. Household level synthetic populations are seen as an advantage in transport modelling because of the interdependence of travel capabilities amongst household members (e.g. Beckman et al., 1996).

There are some methodological innovations in spatial microsimulation which were not used in this first iteration of the indicator (examples are given in the next section). Though this is a limitation, it was felt more important to produce a complete application of the indicator, taking some account of a wide range of factors rather than focussing solely on one aspect of the modelling process and having to reduce the range of factors considered. The modelling process is static. Whilst building the indicator from scratch with say the 2001 census data and the 2011 census data does give some opportunity to assess change over time it is a limited snapshot of change.

10.5 Further work

Some areas of further work have already been alluded to in Section 10.4. Further work could investigate what improvement in the performance of the spatial microsimulation is possible by testing the effect of different innovations. This testing stage would be particularly useful if the modelling process is to be applied to other datasets or to other indicators. Examples of spatial microsimulation innovations which could be investigated are firstly: The construction of multiple synthetic populations following the method of Smith et al., (2009), who built several synthetic populations and allocated the most realistic synthetic population to Output Areas in Leeds and Bradford. In stage 2 of the spatial microsimulation, the modified Monte-Carlo sampling procedure reported in Williamson, (2012) may reduce the stochastic variation introduced in this part of the modelling process.

The level of error and uncertainty in the modelling process could be reduced by gathering better data on the circuity of the network at a reasonably fine resolution across the UK. Gathering or accessing data on the types of bikes in the UK bike fleet which is connected to socio-demographic data would allow better account to be taken of bicycle type. A household based model suggests improvements as mentioned in Section10.4, but reconstructing the modelling process in this form would involve significant work. Before rebuilding there also needs to be a consideration of which extra household level attributes should be considered and how they might address limitations.

10.5.1 Assessing other policies

Flexibility and ease of use of the modelling process and results discussed in Section 9.8.1 and Section 10.2 extends to examining other scenarios and policies. There may be policies which an authority wishes to test which require more data. The modelling process can be adapted and other attributes could be included in the spatial microsimulation. Two examples of other policies which could be examined are given below:

An authority is appraising a policy to decrease travel time. Trip estimation models predict induced demand for more longer trips. This policy would decrease the number of people with the capacity to commute by active modes and therefore have a negative impact on resilience. The Indicator devised in this thesis could be a useful input to the planning process to more effectively show dis-benefits of shortening travel time.

A new residential development is proposed. The size and specification of the houses can be used to estimate what the population of the area would be like. The indicator could then be used to estimate the adaptive capacity of the potential population of the new development. A new development with very low adaptive capacity may need to be altered or relocated.

10.5.2 Assessing other scenarios

In this thesis the assumption is made that a fuel shock occurs and that as a result, no motorised transport is available for commuting. Further fuel availability situations could be considered such as

A. There is a very limited supply of fuel. This fuel is only available for the transport of essential workers to and from work by some form of motorised transport.

B. There is slightly more fuel available than in A. There is fuel available to transport essential workers as above, but there is also some fuel available to

> power some public transport; commuter trains would operate and a bus service would operate to move workers to and from work. Even in scenario B the amount of fuel available is far less than at the current time and many people are expected to have to rely on walking and cycling.

To calculate the indicator for these alternative scenarios other factors would have to be considered. The acceptability of cycling should considered because the scope of the indicator (see Section 4.2) states that capacity should be estimated on what is safe and healthy for individuals. (Parkin et al., 2007b) presented a logit model of acceptability of cycling; the probability that an individual will find it acceptable to cycle. The parameters in Parkin's model are: proportion of the network with cycling facilities, as well as age and gender distribution of the population. Parkin's model is independent of changes in speed, volume and ratio of bicycles to motor vehicles, which would change immediately after a shock. In alternative scenarios A and B, there are some motor vehicles on the road so it is assumed that bicycles will have to stop at intersections. Because it requires more energy to accelerate after stopping it reduces the distance which can be covered within the time budget (Parkin, 2008; Parkin and Rotheram, 2010; Wilson, 2004). A simplifying assumption could be made that approximately 10% of the workforce would be classed as essential workers, or a more detailed methodology could try to ascertain which workers would be deemed essential. In alternative scenario B a model of public transport availability would have to be integrated with the model. The model could again be based on simplifying assumptions or a more detailed methodology.

10.5.3 An indicator of capacity to make other journeys

As stated in Section 10.4 the modelling process appears suited to modelling the capacity to make other journeys. A first consideration in doing so would be to gather data on location of key activities and services such as those used in the DfT accessibility measures (DfT, 2010c). Not all location is released by the DfT ; some such as supermarket location is commercially copyrighted. However there are open data sources from which such information may be collected. A bigger challenge is determining a method of which service a particular individual may access. For example a person's socio-economic status my influence which supermarkets they can afford to shop at. In the UK children do not always attend the closest school. If the assumption is upheld (as set out in Section 4.2) that people will need to go where they currently go immediately after a fuel shock, then the method of determining travel distances will be more difficult. If this can be dealt with, it does offer an opportunity for further models. Because distinct origins and destinations will be used, the actual network routes can be used. This will remove the need for assumptions about slope profile discussed in Section 7.4.5.

10.5.4 Integration with accessibility measurement tools

The ability to access shops, education and other services assessed by accessibility planning would be a ready application of the modelling process. Accessibility is an important goal in government transport planning (DfT, 2009b). Accessibility is seen as important because it is linked to deprivation and social exclusion[55] (Lucas and Jones, 2012; SEU, 2003) as well as sustainability (Gudmundsson and Höjer, 1996; Vega, 2012). A fuel shock could reduce the accessibility of people wanting to get to places to take part in the activities that occur there. The potential consequences of loss of accessibility are summarised by Lucas (2012). They are loss of accessibility to the following: Goods; Services; Decision making; Social capital; Social networks; Life chances; (Lucas 2012 p107). Though this thesis has been concerned with the development of adaptive capacity to fuel shocks, the modelling process may be used as a basis for improving accessibility indicators currently in use. As explained in Section 3.1.2, current measure of accessibility by walking and cycling do not take account of the physical capabilities of individuals. An adapted version of the modelling process could contribute to models of accessibility which take a more realistic view of the travel constraints faced by individuals.

10.5.5 Development of the modelling process

As explained in Section 4.2, defining the situation of interest is a separate process to that of indicator estimation. If future work requires a predictive model of individual attributes several years into the future (which was beyond the scope of this thesis), dynamic spatial microsimulation may be useful.

To eventually develop a dynamic spatial microsimulation, a staged approach is useful. For example (Ballas et al., 2006) appear to have used a staged approach to develop a dynamic spatial microsimulation model. They first generated a population for the current time using a static spatial

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[55] "Social exclusion is a constraints-based process which causes individuals or groups not to participate in the normal activities of the society in which they are residents and has important spatial manifestations." (Preston and Rajé, 2007 p151).

microsimulation. This base case population helped them to identify and address challenges of estimating changes in the population over time.

The development of a dynamic spatial microsimulation for a future forecast of adaptive capacity to fuel shocks would face the following additional challenges. Dynamic spatial microsimulation would require a set of rules for updating each attribute at each time step. Some of these may be straightforward such as:

Each year add 1 to the age of each individual

Slightly more complicated is determining whether a person gives birth to a child or dies. This would require a stochastic modelling process (see for example Wu and Birkin, 2012). More complex than this is modelling the level of anticipatory response to a future fuel shock and how this may affect individual attributes such as bike ownership, commute distance and even fitness. The assumptions behind this aspect of a dynamic spatial microsimulation would require speculation beyond the scope of this thesis. For practical reasons illustrated above, creating a static base case and policy case indicator represented a clearly defined stage in work to develop walking and cycling indicators of resilience to fuel shocks, and sits within the scope defined in Section 4.2. It does however create interesting questions and challenges for further work.

Demographic and agent based models may be used to age, migrate and change the health and socioeconomic characteristics of individuals over time. This would allow estimations of the indicator projected into the future. Results of this nature would be interesting, but this requires greater speculation about the future than was allowed in this research. Agent Based Models may also be used to investigate scenarios involving the interaction of different forms of resilience. They may also be used in estimating other forms of adaptive capacity which would come into play in the medium term after a shock. For example, the interaction between being unable to make journeys immediately after a fuel shock with the need to change jobs or move home in the medium term. This type of modelling would require household level population synthesis to better estimate the effect that household members have on each other's mobility.

10.5.6 Engaging with planners and practitioners

The indicator has been developed to a point where its potential usefulness could be assessed by demonstrating it to practitioners. Some form of workshop testing outputs and developing useful scenarios may be of use in developing the policy relevance of the indicator.

10.5.7 Engaging with Transport Geography

In Section 9.5 the indicator was linked to other indicators, the Output Area Classification and the Index of Multiple Deprivation. These links create the opportunity to develop a narrative of what might happen to some of the people in particular places. That aids discussion of what *could* happen and *could* be done by policy makers, practitioners, residents and other groups. It shows that the indicator can be used to develop what was referred to in the Section 3.2.3.1 as a “constructivist – discursive - function” (Boulanger, 2007). Work which has developed narratives of what might happen in particular places has been used as a basis for research that engages practitioners in thinking about radically different transport futures involving greater use of walking and cycling (e.g. Tight et al., 2011). This indicator’s discursive function may aid that process.

A quantitative indicator contextualised in terms of social classification or measures of deprivation could be a start point for deeper analysis of some of the social processes which are linked to vulnerability to fuel shocks. An example of applying this approach is found in Lovelace and Philips, (2014). Firstly they took an example of relevant theory examining social processes, mobilities theory (Urry, 2007). Mobilities theory is concerned with all types of movement and how that influences the society. It is an attempt to understand how people benefit from or are affected by movement or lack of (Hannam et al., 2006) Mobilities theory (Sheller, 2008; Sheller and Urry, 2006) is argued to be an important tool in understanding transport geography (e.g Goetz, 2006; Hanson, 2006). The reason for this is it accounts for the social processes that cause people to be able to take part in society as a result of being able to harness movement of themselves, objects and information (Hannam et al., 2006). A concept within Mobilities theory is network capital. Network capital is:

> *“the capacity to engender and sustain social relations with those people who are not necessarily proximate and which generates emotional, financial and practical benefit (although this will often entail various objects and technologies or the means of networking)” (Urry, 2007) p197*

Network Capital is derived from eight groups of objects and physical capacities that allow movement and accessibility. These are: *1. Array of travel documents; 2. Network of others at a distance who offer invites; 3. Movement capacities; 4. Location free information and contact points; 5.*

Communication devices; 6. Appropriate, safe and secure meeting places; 7. Access to car, roadspace, fuel, lifts, aircraft, trains, ships, taxis, busses, trams, minibuses, email account, internet , telephone and so on; 8. Time and other resources to manage and coordinate 1-7 (source Urry 2007 P197-198). Lovelace and Philips, (2014) described hypothetical individuals living in particular zones in terms of their *network capital*. There follows a short example of this method applied to individuals in the case study built in this thesis. It illustrates a possibility for further research:

Consider the following individual; an affluent person living a town such as Harrogate who currently commutes 30km to Leeds. They are unable to make this commute every day by bike. This can be discerned by the model. This person is also unaffected by policies; they go to the gym and have above average levels of fitness for their age. They also own a bicycle and do not need to escort children to school. According to the raw policy case indicator, this person (and others like them living in the same OA or LSOA) is vulnerable. There is an argument based solely on the indicator to develop further policies to help them. However with some contextual information, such as the fact they live in a “Prospering Suburbs” OA or a low deprivation LSOA, more insight is gained to help decision makers. Thinking in terms of Urry’s notion of network capital, there are some qualitative insights which could be gained as to their overall resilience to fuel shocks. The concept of Network Capital suggests that those from more affluent areas have more affluent and influential contacts. This social network could be put to use to help this person adapt. Affluent people have more financial resources so this may be used to rent an apartment in Leeds so the journey to work does not have to be made every day. Many of the most affluent are professionals who have a degree of control over their working schedules. Again this resource may be used to adapt by changing work practices so they can work from home.

Consider now a less affluent older worker living in an Output Area “constrained by circumstances” in a former Yorkshire mining village. Their commute though only 10km is longer than they are physically capable of. They are less likely to have financial resources to rent week time accommodation near work, less likely to have influential contacts to help them make adaptive lifestyle changes and due to having a job requiring being on-site at particular times a switch to home working is not possible. These are just simple hypothetical examples using the principle of Network Capital. It is a qualitative extension of the modelling process and one possible avenue to explore the reasons for people and places being resilient or vulnerable to fuel shocks. Interpreting results in this way requires what (Lovelace and Philips, 2014) call a “humble approach” or wariness of the caveats.

10.6 Concluding statement

This thesis concerned the designing, developing methods to calculate and applying a new spatially explicit transport policy indicator which shows: Who could get to work tomorrow by walking and cycling if there was a fuel shock today? The literature reviewed in Chapters 2 and 3 established the potential for fuel shocks and the need for suitable indicators. The research presented has developed conceptually and practical method to calculate the resilience of a population of individuals to fuel shocks. The research case study has shown that existing secondary data can be used to create a spatially detailed indicator of resilience to fuel shocks. The method has been shown to be robust and considerable progress towards a “good – indicator” has been made. The results for England are of concern; our ability to participate in the mobility system is vulnerable to fuel shocks as only 44% of workers could get to work by walking and cycling if they had to. However on a more positive note policies to increase walking and cycling have potential to increase the level of resilience to fuel shocks. The mean raw effect is 23% and when error and uncertainty is accounted for, the policy package discussed in Chapter 9 has a positive effect in 99% of Output Areas. The indicator also discerns and identifies the OAs where individual policies can confidently be assumed to have an effect. The fact that this thesis has identified a problem and steps towards evaluating and addressing it through the transport planning framework is both an original research contribution and grounds for optimism.

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Microsimulation: A Reference Guide for Users. Springer Netherlands, Dordrecht, pp. 171–193.

12 Acknowledgement of data sources

Digital map data from third party sources is used in this thesis. All maps in this thesis have been prepared by Ian Philips, University of Leeds in 2014. UK Boundary data was downloaded from http://borders.edina.ac.uk/html/boundary.html. This data is provided with the support of the ESRC and JISC and uses boundary material which is copyright of the Crown, the Post Office and the ED-LINE consortium. (It Contains National Statistics data © Crown copyright and database right 2012 Contains Ordnance Survey data © Crown copyright and database right 2012).

OS backdrop mapping © Crown Copyright/database right 2014. An Ordnance Survey/EDINA supplied service. The map projection used is GCS_OSGB_1936 British national Grid.

Census data for the 2001 UK census was used. It is provided by Office for National Statistics, 2001 Census: Aggregate data (England and Wales) UK Data Service Census Support. Downloaded from: http://casweb.mimas.ac.uk This information is licensed under the terms of the Open Government Licence [http://www.nationalarchives.gov.uk/doc/open-government-licence/version/2]

Data from the Health Survey for England was used in this thesis. Its source is the National Centre for Social Research and University College London. Department of Epidemiology and Public Health, *Health Survey for England, 2008* [computer file]. *3rd Edition.* Colchester, Essex: UK Data Archive [distributor], July 2011. SN: 6397 , http://dx.doi.org/10.5255/UKDA-SN-6397-1 Crown copyright material is reproduced with the permission of the Controller of HMSO and the Queen's Printer for Scotland.

Data from the UK National Travel Survey is accessed through the UKDA. Department for Transport, National Travel Survey, 2002-2010 [computer file]. 7th Edition. Colchester, Essex: UK Data Archive [distributor], April 2012. SN: 5340 , http://dx.doi.org/10.5255/UKDA-SN-5340-3

All other data sources are cited in the text

13 List of Abbreviations

Abbreviation	Term
CRR	Coefficient of Rolling Resistance
CO	Combinatorial Optimization
CRN	Common Random Numbers
CBA	Cost Benefit Analysis
DfT	Department for Transport (UK)
DR	Deterministic Reweighting
DEM	Digital Elevation Model
FMF	Flexible Modelling Framework
GOR	Government Office Region
HSE	Health Survey for England
IMD	Index of Multiple Deprivation
IPF	Iterative Proportional Fitting
LT	Lactate Threshold
LAD	Local Authority District
LSOA	Lower layer Super Output Area
MSOA	Middle layer Super Output Area
MAUP	Modifiable Unit Areal Problem
MCA	Multi-Criteria Analysis
NAP	National Adaptation Plan
NEP-F	National Emergency Plan –Fuel
NS-SEC	National Statistics-Socio Economic Classification
NTS	National Travel Survey (UK)
OA	Output Area
OAC	Output Area Classification
OBLA	Onset of Blood Lactate Accumulation
RMSE	Root Mean Square Error
SA	Simulated Annealing
SAE	Standardised Absolute Error
SR	Synthetic Reconstruction
TAE	Total Absolute Error
UA	Unitary Authority
VO2	Volume of Oxygen

14 Appendix 8.1 Slope profile test

Results of a small test exploring the distance between peaks and changes of slope which a walker of cyclist might encounter in an English urban area when travelling towards or away from the city centre. The routes were plotted over Ordnance Survey 1:50,000 maps in MemoryMap software.

location	route length	total ascent	total descent	peaks	route direction	dist to first change of slope	dist from last change of slope	km between hills
Bristol	9.76	138	79	5	N	1	1	1.95
Bristol	11.3	129	92	3	NW	2.5	0.5	3.77
Bristol	11.9	260	180	7	E & SE	0.3	2	1.70
Bristol	5.7	112	40	3	S	0.8	3	1.90
Bristol	15.4	267	201	5	SW	0.8	1.4	3.08
Bristol	11.7	235	105	6	W	0.5	0.2	1.95
Bristol	13.3	304	302	6	NW	0.4	3.6	2.22
London	5.96	52	30	3	N	0.5	0.3	1.99
London	5.81	7	3	1	NW	3	2.81	5.81
London	4.66	8	13	2	S	0.25	4.25	2.33
London	5.19	39	31	4	E	0.6	0.9	1.30
London	12.2	156	94	2	NW	1.5	0.5	6.10
London	15.7	113	65	4	SE	6.5	0.6	3.93
Birmingham	20.5	117	116	5	N-S	1	1.4	4.10
Birmingham	21.2	344	311	9	E	1.5	1.7	2.36
Birmingham	14	114	135	5	E	0.4	0.2	2.80
Birmingham	11	68	75	3	SE	1	2	3.67
Derby	5.47	12	36	2	SE	2	2.5	2.74

Derby	4.47	47	83	3	NE	0.4	0.5	1.49
Derby	5.05	77	39	4	NW	0.25	0.6	1.26
Derby	5.07	62	32	3	SW	0.25	0.25	1.69
Cambridge	20.1	48	64	3	S-N	2	1.5	6.70
Cambridge	11	39	32	3	E	1.6	4	3.67
Cambridge	12.5	34	26	2	NW	0.4	2.5	6.25
Sheffield	7.23	205	31	2	W	6.5	0.5	3.62
Sheffield	11.1	251	253	4	SE	3.5	1.1	2.78
Manchester	11.6	162	95	4	NW	3	1.6	2.90
Manchester	13	239	39	2	NE	0.5	12	6.50
Manchester	10.5	42	30	5	S	0.7	1.5	2.10
York	14.8	86	77	5	S-E	0.7	1.8	2.96
Leeds	27.1	362	356	11	N	0.5	0.7	2.46
Leeds	7.69	128	49	2	NE	2.5	0.7	3.85
Leeds	11.3	155	81	3	S	3	0.4	3.77
Newcastle	13.7	95	133	5	W	0.5	3.7	2.74
Newcastle	11.2	80	48	4	N	0.5	1.2	2.80
Newcastle	1.05	136	112	6	SE	0.8	1	0.18
Huddersfield	20.7	678	594	12	S-N	3	0.7	1.73
Huddersfield	23.5	240	385	8	W-E	1	3.5	2.94
Total	443.4							
Mean		148.4	117.6			1.6		3.1

15 Appendix 9.1
Summary of Output Area Classification

Source: (Vickers and Pritchard, 2010 p412 -413) [56]

[56] Not to be included in an e-thesis for copyright reasons.

16 Appendix 9.2 District resolution map and cartogram with colour scheme comparable with OA resolution

Defined interval (e.g. breaks at 10, 20 30% etc) is used so that map colour is consistent between OA and district maps.

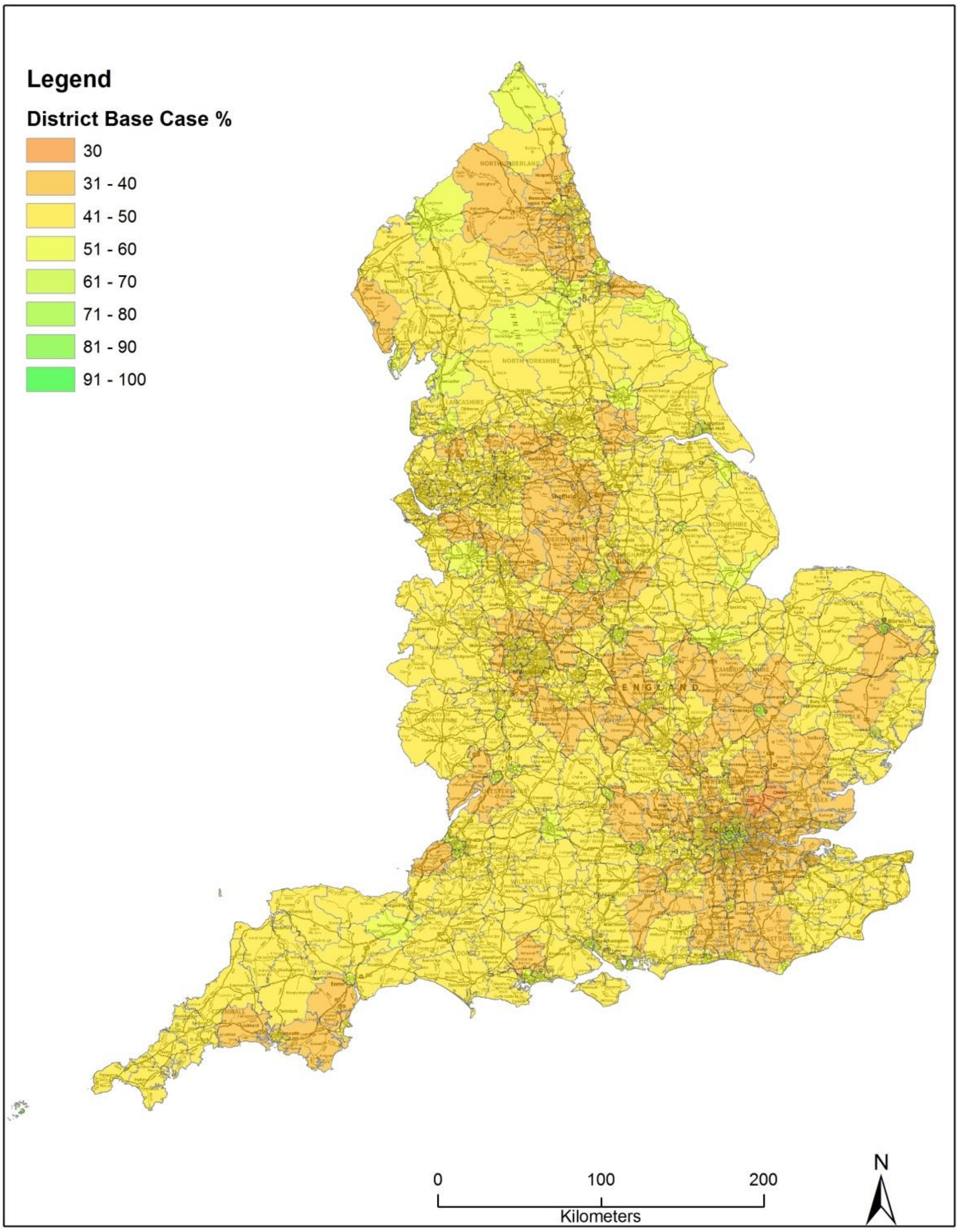

Figure app 9.2.1 Base case indicator value at district resolution for comparison with OA maps

The colour scheme is consistent with the LSOA and OA maps but the data is the same as shown in Figures 9.4 and 9.5. Values are percentages of the number of people in each district who could commute to work by walking and cycling in a traffic network with no motor vehicles.

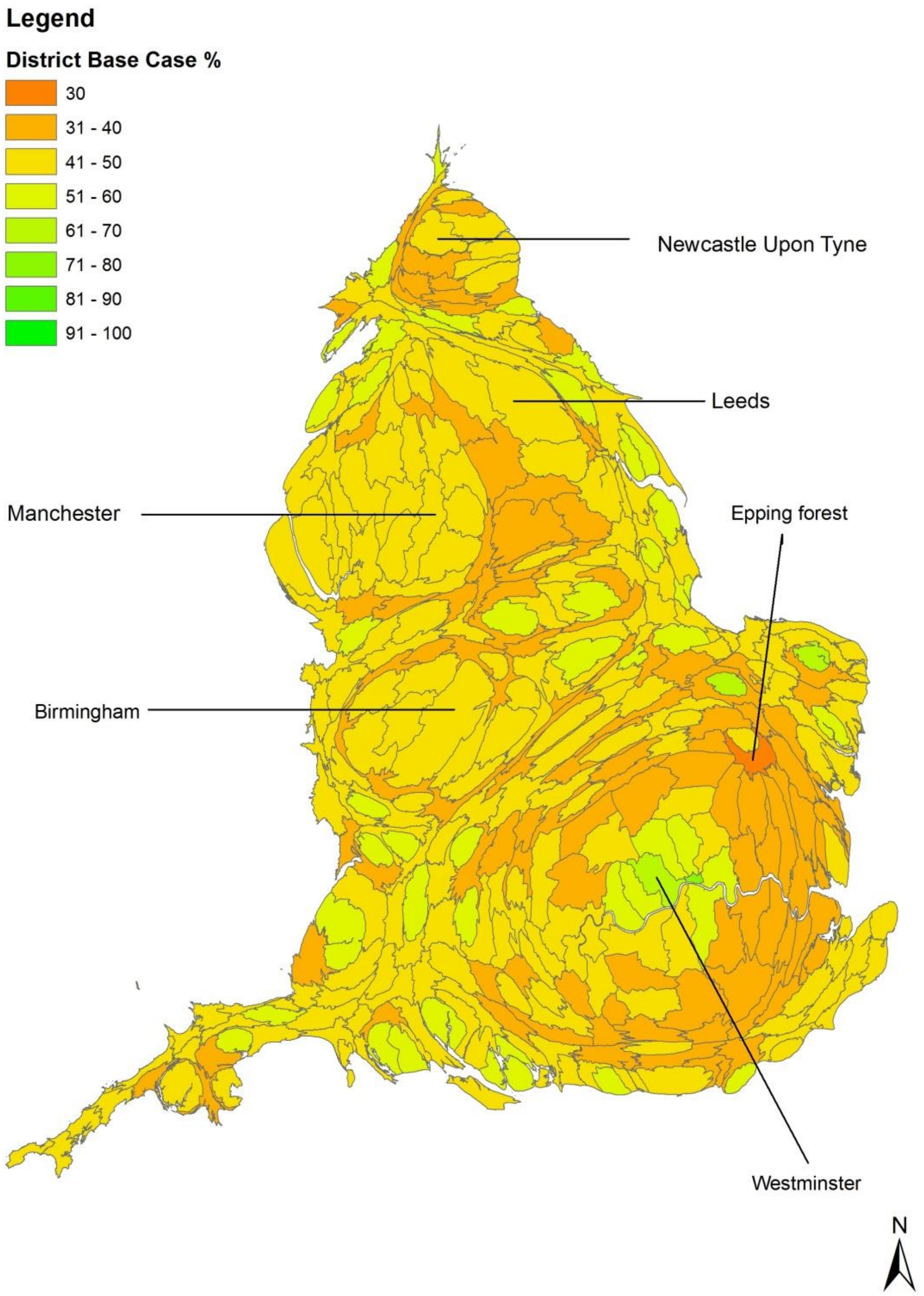

Figure app 9.2.2 Base case indicator value at district resolution for comparison with OA maps.