# Modelling the Environmental Justice of the Spatial Distribution of Air Quality

by James O'Brien, BSc (Hons.), MSc

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School of Engineering

Newcastle University

Abstract

Relationships between air pollution, health and deprivation potentially result in the highest cost to both the public and the government in terms of increased mortality and morbidity; hence establishing links between them is important and justifiable. The concept of Environmental Justice (EJ) questions whether certain socio-economic groups bear a disproportionate burden of environmental externalities, and whether policy and practice are equitable and fair.

This research presents an innovative air quality modelling framework to map the EJ of the spatial distribution of air quality; and the impact of air quality management measures on existing EJ concerns. To assist in this goal, a modelling approached has been developed which enables the assessment of traffic management solutions that may create only subtle changes in the traffic flow regimes; and accurately assesses the impact of a reduction in vehicle kilometres travelled (VKT).

Strong evidence of environmental injustice in the current distribution and production of poor air quality has been provided in the literature. However, the overwhelming majority of existing studies have concentrated on the analysis of current or historic associations. As a result their methodologies do not allow for the analysis of future strategies therefore, a gap exists in understanding the EJ implications of air quality strategies or schemes designed to improve air quality.

Recent years have seen heightened political focus on policy and attempts to improve air quality. Whilst it is broadly suggested in the literature that improving air quality also will improve existing EJ concerns, evidence to date shows that even in situations where air quality is improving, the rate of concentration improvement is lowest for the poor.

This research presents a suite of linked models of traffic, emission, dispersion, and geodemographic models (the modelling framework) that together allow not only more accurate assessment of the existing EJ situation to be established over using traditional techniques, but also the assessment of future air quality strategies and schemes designed to improve air quality which may improve or exacerbate the existing EJ relationship.

The use of microsimulation traffic modelling in conjunction with an instantaneous emissions model (IEM) is a well-established emissions modelling technique. However, the use of IEMs is generally confined to exploration of emissions outputs and not the subsequent dispersion of emissions in order to determine air quality. This research successfully combines advanced microscale modelling techniques and applies them in the context of an EJ study in order to produce an original modelling framework capable of household level EJ analysis.

This research has established that, at a city level, there is no linear relationship between air quality and deprivation in the North East cities of Durham, Newcastle and Gateshead. However, analysis of geodemographic data at the household and postcode levels has provided evidence of environmental injustice in air quality across all three study areas.

Additionally, this research has explored the impact of reductions in VKT as a proposed air quality management measure. Thereby, the reductions required in VKT (over 2010 traffic flows) in one study area, Durham, have been established in order to meet both EU air quality limits and future carbon targets.

Incremented 5% VKT reduction changes were made to the base-case 2010 scenario until all considered targets were met. Based on a 2010 vehicle fleet, a 50% reduction in traffic through Durham's AQMA is required to meet all EU air quality targets. Similarly, a 25% reduction in VKT is required assuming a 2020 vehicle fleet, and by 2025 a 15% reduction in VKT would ensure Durham met its air quality targets. Moreover, a 10% reduction in VKT by 2020, and 25% reduction by 2025 would ensure carbon dioxide ($CO_2$) reductions across the study area equal to those set out in the carbon budget.

Furthermore, it has been established that the reductions in VKT to meet both EU air quality limits and future carbon targets eliminates the identified EJ issue in Durham. Moreover, if future VKT is constrained to 2010 levels, the spatial distribution of air quality will be environmentally just in both the 2020 and 2025 assessment years.

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## Table of Figures

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## List of Accompanying Materials

### The following journal paper has been published:

O'Brien, J., Namdeo, A., Bell, M. C., Goodman, P. (2013b) 'A congestion sensitive approach to modelling road networks for air quality management', International Journal of Environment and Pollution (IJEP). Vol. 54, Nos. 2/3/4, 2014.

O'Brien, J., Namdeo, A., Bell, M. C., Goodman, P. 'Environmental justice and air quality strategies in Durham', Transportation Planning and Technology (paper under review).

### The following conference papers were published during the PhD:

O'Brien, J. (2014) 'Environmental justice and air quality strategies in Durham', Proceedings of the 46th UTSG Conference Newcastle.

O'Brien, J., Namdeo, A., Bell, M. C. (2013) 'Modelling the Environmental Justice of the spatial distribution of Air Quality', Proceedings of the 45th UTSG Conference Oxford.

O'Brien, J., Namdeo, A., Bell M. C. (2012) 'Modelling the Environmental Justice of the spatial distribution of Air Quality', Proceedings of the 44th UTSG Conference Aberdeen.

O'Brien, J., Bell, M., Namdeo, A., Sinclair, M., Scaife, D. (2012) 'An approach to modelling road networks for air quality management', 17th JCT Traffic Signal Symposium, University of Warwick.

### The following news reporting was published during the PhD:

Nelson, B. (2014) ''Better way to monitor traffic fumes', Durham Times, 15 December 2014. Available at: http://www.durhamtimes.co.uk/news/11667918._Better_way__to_monitor_traffic_fumes/ (accessed 06/01/2017).

Henderson, T. (2014) 'Newcastle University say traffic pollution could be up to 60% worse than thought', Chronical Live, 15 December 2014. Available at: http://www.chroniclelive.co.uk/news/north-east-news/newcastle-university-say-traffic-pollution-8292212 (accessed 06/01/2017).

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CHAPTER 1

# 1. Introduction

This research presents a robust air quality modelling framework to map the Environmental Justice (EJ) of the spatial distribution of air quality; and the impact of air quality management measures on existing EJ concerns. Whilst the concept of EJ has a significant history, it has gained in prevalence in recent years as social goals (e.g. equity, fairness, and justice) have themselves gained greater prominence through almost universal efforts to promote sustainable development (Namdeo and Stringer, 2008). The concept draws attention to the questions of whether certain socio-economic groups, including the economically and politically disadvantaged, bear a disproportionate burden of environmental externalities, and whether policy and practice are equitable and fair (Wilkinson, 1998; Stewart et al., 2015; Mitchell et al., 2015; Moreno-Jiménez et al., 2016).

Relationships between air pollution, health and deprivation potentially result in the highest cost to both the public and the government in terms of increased mortality and morbidity; hence establishing links between them is important and justifiable. Recent analysis of EJ at the national level in the UK has produced evidence of environmental injustice in the distribution and production of poor air quality (Mitchell et al., 2015). "Those living in the most deprived parts of England experience the worst air quality" (Pye et al., 2006).

This research aims to map the EJ of the spatial distribution of air quality across the study area, the North East of England. Three case study North East cities, Durham, Newcastle and Gateshead have been compared and contrasted to allow more definitive findings and greater assurance that the established modelling framework can be applied across different locations and scales. The areas of study were predefined as a result of research links within the North East region, specifically, Durham, where funding to support the research was obtained through Durham County Council (DCC). Additionally, a North East context was present as a result of the researcher's connection with the SElf Conserving URban Environments (SECURE) project. The SECURE project sought to develop a Regional Urbanisation Model that synthesises resource-supply-demand-waste systems from city and local authorities to regional scales via the integration of three themes - Urbanisation (land use and transport), Building and Energy (supply and demand) and Ecosystem Services (the benefits humans receive from ecosystems). Due to the timeframes of the project, this research was unable to utilise outputs from the project. However, connections with the work allowed access to the North East regional transport model (Section 3.4.1) gave the work a wider geographical background and an opportunity to test the framework in other North East cities.

A nested modelling approach has been adopted to allow the EJ investigation to be conducted across scales, using microscale, mesoscale and strategic modelling (Section 2.9). At the most detailed level to increase understanding of local level interactions, a finer microscale resolution has been undertaken in the City of Durham.

In May 2011 an Air Quality Management Area (AQMA) was declared as a result of failure to meet the annual mean objective/ EU limit value for Nitrogen Dioxide ($NO_2$). Consequently DCC worked to produce an Air Quality Action Plan, developing strategies to improve air quality within the AQMA. The Air Quality Action Plan was approved in June 2016, after the scenario testing element of this research was completed. The plan includes an action regarding the "introduction of a (Urban Traffic Management Control) UTMC or (Split Cycle Offset Optimisation Technique) SCOOT system to coordinate traffic through a network of junctions within Durham City and reduce congestion." (Durham County Council, 2016). The inclusion of this action was, in part, a result of this research, following a DCC review of the findings of the microscale scheme testing, which gave confidence that a SCOOT system could contribute to an overall reduction in oxides of nitrogen (NOx, the collective name for all compounds formed by the combination of oxygen with nitrogen when fuel is burnt) across the AQMA (Section 6.2.1).

To compare and contrast findings from the Durham microscale study, a mesoscale study of Newcastle upon Tyne and Gateshead provided insight in to the EJ of these areas, as well as determining the suitability of the modelling framework at different scales. Finally, the results for the study of Newcastle upon Tyne and Gateshead allowed the most appropriate scale modelling approach to be identified, ensuring that the most appropriate methodology for modelling the remaining study areas was applied.

When analysing air quality and EJ it is important to consider other factors that may be relevant to the relationship. For example, when considering the link between health and environmental justice, external factors such as air quality are an acknowledged and serious contribution to respiratory health (Walker, 2012). However, the mechanisms that lead to respiratory illness are vast, from early interactions with infectious agents such as viruses, bacterial infections, to an individual's composition of the respiratory microbiome (Unger and Bogaert, 2017). In combination with individual general health, lifestyle choices such as prevalence of smoking, and general population demographics including age and gender, the number of potential confounding factors of consideration is significantly beyond what could reasonably be expected to be explored; and the prevalence of suitable data is a substantial limitation should such work ever be attempted. Furthermore, despite significant advances in medical research and understanding of respiratory illness, there are still significant knowledge gaps in understanding cause and effect. For example, the importance of other underlying health issues, including mental health, has only recently been understood; individuals with mental illness have an increased risk of a wide range of illness including respiratory disease (Chadwick et al., 2016).

Similarly, evidence of historic pollution induced neighbourhood sorting has been presented for many UK and world-wide cities, for example, Heblich et al. (2016) analysed 10,000 industrial chimneys in 70 English cities around the year 1880 and used terrain and wind patterns to predict where their smoke would have drifted to show the presence of pollution induced neighbourhood sorting. However, in reality the patterns that lead to areas of 'poor' and 'wealthy' areas in our urban spaces is hugely complex and varied, with geography (rivers, topography), natural resources (industry) and land type (building) among many contributing factors which determine where people live and the relationship between air quality and EJ.

Finally, the interaction with wider environmental inequalities should be considered. Numerous physical and social barriers represent issues of EJ, for example, access to walkable streets and park areas; and proximity to hazardous waste facilities, contaminated food sources, and agricultural pesticides (Cutts et al., 2009; Fecht et al., 2015). These above points are expanded on in the literature review in Section 2.5.2.

However, despite this complex relationship, existing research has found that air quality is an EJ issue, with poorer neighbourhoods more likely to face greater pollution. Attempts to gain greater understanding of this relationship, and model strategies that may improve or exacerbate the existing EJ relationship are therefore very valid, with the potential to aid decision making and address inequality issues a valued goal.

### 1.1 Rationale for the research project

The global increase in demand for road transport has resulted in the deterioration of air quality in the world's cities (Mayer, 1999; DEFRA, 2011; World Health Organisation, 2016). Today the major threat to clean air in urban areas is posed by traffic emissions (DEFRA, 2011; Kelly and Fussell, 2015). Petrol and diesel-engine vehicles emit a wide variety of pollutants, principally carbon monoxide (CO), oxides of nitrogen (NOx, the collective name for all compounds formed by the combination of oxygen with nitrogen when fuel is burnt), volatile organic compounds (VOCs) and particulate matter (PM) (DEFRA, 2011).

Health has emerged as an important driver for air quality policy (DOH, 2010; Bell et al., 2012; Cartier et al., 2015). Research which establishes links between air quality, health and EJ will enable a new emphasis on the importance of air quality policy. It is hoped that a renewed understanding of this relationship and EJ concepts can aid the step change in human behaviour that is required if current air quality and health policy aspirations are to be realised.

In economic terms the Environmental Audit Committee (EAC) noted that failure to tackle current air quality issues is putting the NHS under unnecessary strain and the UK is exposed to the potential of fines that could reach £300 million, dependant on rulings from the European Court of Justice (ECJ) (EAC, 2010; Neslen, 2018). Therefore work to best derive air quality strategies is of real relevance.

The impact of anthropogenic Greenhouse Gas (GHG) emissions on the Earth's climate is also a significant environmental concern (IPCC, 2014). The 2014 report from the Intergovernmental Panel on Climate Change (IPCC) concluded that it is "extremely likely that more than half of the observed increase in global average surface temperature from 1951 to 2010 was caused by the anthropogenic increase in GHG concentrations”. Unfortunately the road transport sector has seen a continued increase in GHG emissions in recent history (IPCC, 2014). Consequently governing bodies across the globe are, through legislation, obligated to develop and implement strategies to reduce air pollution and GHG emissions from all sources including road transport, for example, the Kyoto Protocol (UNFCCC, 1998).

It is becoming increasingly apparent from recent policy that, while addressing the GHG abatement agenda, existing policies could be exacerbating local and regional air pollution (EC, 2015). This exacerbation can occur directly through ‘win-lose’ measures e.g. dieselisation of the UK vehicle fleet; diesel vehicles typically have lower carbon dioxide ($CO_{2)}$ emissions than petrol vehicles due to the lower carbon content of diesel fuel (Boultier et al., 2007). However, diesel vehicles are also generally associated with higher NOx, f-$NO_2$ and $PM_{2.5}$ emissions than petrol vehicles (f-$NO_2$ is the fraction emitted directly as $NO_2$, different vehicle types emit different proportions of NOx as $NO_{2)}$ (Rhys-Tyler et al., 2011). Alternatively, indirect exacerbation can occur as a result of emphasis on carbon and GHG emissions detracting from air quality agendas.

Air quality has gained significant momentum in recent years as a political issue, largely as a result of the increased understanding of the health implications of air pollution, and also as a result of high profile news events such as the emissions scandal and London’s attempts to meet its statutory air quality targets (Section 2.2). However, there remains growing concern that losing sight of air quality goals through the prominence of $CO_2$ and climate change agendas may result in failure to meet targets in both areas (EAC, 2010). A key provision of the Climate Change Act in 2008 was a legally binding target of at least an 80 percent cut in $CO_2$ emissions by 2050. This is to be achieved through action in the UK against a 1990 baseline. Of particular importance to this research are interim targets proposed by the Committee on Climate Change (CCC) for 2020 and 2025 (18 percent and 32 percent reductions in emissions from 2010 respectively) (CCC, 2010). In light of this agenda, the focus of existing and emerging legislation has been placed on developing and implementing low carbon strategies across all sectors on a national scale (DECC, 2011; DfT, 2011; EC, 2011). Thereby, this research will look at the impact of targeting $CO_2$ objectives as a transport strategy, and discuss whether this satisfies air quality goals in the study area.

The review of the implications of the UK's likely exit from the European Union on air quality legislation in Chapter 2, Section 2.3 would suggest that there is limited risk of disruption given that even the UK's existing Air Quality Objectives are said to be at least as stringent as the limit values of the relevant EU Directives (Upton, 2017).

Nonetheless, there is potential for focus to shift further away from meeting specific EU set air quality limit values, in favour of more objective regulation under the Air Quality (England) Regulations 2000. Whilst it is vital that efforts to reduce air pollution are maintained, this represents an opportunity for new policy to provide renewed emphasis on objective goals which, it is argued in this research, should include a drive for promoting transport solutions and strategies which enhance social equality in the spatial distribution of air quality.

## 1.2 Research questions, Aims and Objectives of the Research

The research questions, specific aims, and detailed objectives of this research are described in the following two subsections.

### 1.2.1 Research questions

This research has two research questions:

1. To what extent is the spatial distribution of air quality in the identified study areas environmentally just?
2. To what extent do the modelled air quality and carbon reduction transport strategies improve or exacerbate existing EJ concerns?

### 1.2.2 Aims and Objectives

This research has two aims:

1. To establish a modelling framework to explore the research themes and test the EJ of the distribution of air quality across scales within the study area (develop the base-case).
2. To apply the modelling framework to transport strategies and assess the extent to which these actions improve or exacerbate existing EJ concerns (scenario testing).

The modelling framework is a series of linked traffic, emissions, air quality, and demographic models successfully incorporated into a bespoke tool capable of exploring the research themes. The framework utilises varied methods and data sources to model across scales, including the use of an instantaneous emissions model (IEM) and bespoke programming to enable emissions outputs from microsimulation modelling to allow the assessment of air quality strategies that may create only subtle changes in the traffic flow regimes (Grote et al., 2016). Moreover, the innovative use of geocoded geodemographic data in conjunction with the modelled air quality outputs has allowed the existing EJ situation to be established; and the impact of traffic flow regime change on EJ to be more accurately assessed than in previous EJ research. The intention of this research is not to suggest a causal relationship between air pollution health and environmental injustice but to indicate the vulnerability of the populations encountering this environmental burden.

Furthermore, the impact of both air quality management measures and required reductions in vehicle kilometres travelled (VKT) to meet proposed carbon targets on existing EJ concerns are to be assessed.

In addition the research has the following objectives:

- To establish a suitable modelling framework encompassing traffic, emissions and air quality stages to develop a base-case and allow exploration of the research themes;

- To apply the modelling framework to assess the EJ of the spatial distribution of air quality, across scales, within the study areas;

- To investigate the impact of both air quality management measures and required reductions in VKT to meet future EU Air Quality and Low Carbon legislation; and

- To assess the potential to meet both air quality and the proposed carbon targets, in addressing existing EJ concerns.

## 1.3 Thesis Contents

A brief outline of this thesis follows. Chapter 2 introduces the key concepts of air pollution and the relationships between air quality, heath and EJ. The remainder of the chapter provides an extensive literature review of air quality and the impact of road transport emissions to our environment; the role of transport in Greenhouse Emissions and Climate Change; and the EJ implications of transport including the health effects of major pollutants. Additionally, the different methodologies for modelling road transport are discussed, including the distinction between strategic and microscale modelling. The current availability of road transport emissions inventories is explored, and the suitability and accuracy of emissions models discussed. The role of air quality models in predicting air pollutant concentrations is reviewed and commonly used Gaussian air quality dispersion models are critically evaluated. Furthermore, the validation of modelling is discussed and suitable model performance analysis identified. Finally, thoughts are given to air quality and carbon management strategies, including reduction in VKT, aimed at reducing emissions for road transport. The specific importance and range of benefits of reducing the total amount of vehicle use is discussed in detail in Chapter 3.

Following the provision of important background information on the areas of transport, emissions and dispersion modelling; EJ; and road emissions reduction strategies; Chapter 3 describes the methodological approach used in this research. The chapter begins by identifying the research study area and outlining the three North East of England case study cities of Durham, Gateshead and Newcastle. The modelling framework adopted in this research is then documented, with sections on transport; emissions; dispersion; and EJ modelling, guiding the reader through the research approach. The nested nature of the modelling is discussed and for each step of the framework the key data sources and software used are revealed.

The application of the modelling methodology on a microscale case study centred in Durham is presented in Chapter 4. The existing EJ of the spatial distribution of Air Quality in Durham is established. A section on the performance of the models is also provided and a discussion on the impacts of meteorological data, background pollutant data, simulated traffic data, chemical reaction schemes and emissions factors on air quality model performance is presented. Finally, the limitations of the approach are also presented. Chapter 5 provides the results of the mesoscale studies across all three of the study cities. The implications of the findings for the North East of England are discussed and the restrictions of assessing EJ across scales discussed.

Chapter 6 investigates the impact of both air quality and carbon management measures on existing EJ concerns in one of the studied cities, Durham. The impact of reductions in VKT, as well as a traffic engineering scheme, are explored to determine the scale of actions needed to meet legislative targets in the city and the potential they have to alleviate identified environmental injustice in the spatial distribution of Durham's air quality.

Finally, Chapter 7 presents a general discussion on the scope of the research work. Conclusions are drawn on the current state of EJ in the wider North East of England region, and the potential for EJ to act as a mechanism to shape future sustainable policy is discussed. Moreover, recommendations for further research are suggested.

CHAPTER 2

# 2. Literature Review

## 2.1 Introduction

In order to provide background on this thesis a brief overview of the key themes is presented. The contribution to air pollution from road transport sources is discussed at the local, regional and global level; Greenhouse Emissions are discussed in relation to transport emissions; and the concept and history of EJ is established. Specific attention is given to a review of the literature surrounding the relationship between air quality, health and EJ, including a summary of the findings from previous EJ studies. Finally, a review of transport, emissions and dispersion modelling methodologies is presented in relation to air quality studies.

## 2.2 Air Pollution from Road Transport

Up until the 1950s the main air pollution problem in both developed and rapidly industrialising countries was typically high levels of smoke and sulphur dioxide emitted following the combustion of sulphur-containing fossil fuels such as coal, which were used for domestic and industrial purposes (Chen and Goldberg, 2009). However, today the major threat to clean air is posed by traffic emissions (DEFRA, 2011; Kelly and Fussell, 2015). Petrol and diesel-engined motor vehicles emit a wide variety of pollutants, principally CO, NOx, VOCs, which is the name given to a large number of chemicals such as methane ($CH_4$), benzene ($C_6H_6$), 1,3-butadiene ($C_4H_6$), formaldehyde ($CH_2O$) and polycyclic aromatic hydrocarbons (PAHs) (DEFRA, 2010a). Additionally particulate matter (PM) can comprise an array of chemicals including sodium chloride, black carbon, mineral dust, trace metals, water (taken up by a number of secondary particles), VOCs and secondary particles (Hueglin et al., 2005; Vallero, 2008).

Whilst the majority of road transport emissions are from a vehicle tail pipe (Boultier et al., 2012), toxic air pollutants are also released into the atmosphere due to brake and tyre wear (Omstedt et al., 2005), resuspension, and evaporative processes, including leaks in engine casings and tubing (Boultier et al., 2012). Furthermore, some pollutants emitted from vehicles undergo chemical transformations in the atmosphere and are converted to environmentally damaging gases or particles (Vallero, 2008). These emissions are commonly defined as 'indirect emissions' (Cairns, 2013). Indirect emissions, or secondary pollutants, are included in the detailed breakdown of transport related air pollutants found in **Appendix A**. This document provides information on the effects of each pollutant as well as the current policy limits.

Improved road networks, increased car production, less expensive vehicles and increased road construction as a result of 'predict and provide' policy, has made on-road travel more accessible to the world's population (DfT, 2009; Schmidt and Schäfer, 1998). In addition urbanisation has increased and with it the number of people living in cities (UNFCCC, 1998; Fenger, 2009). As a result emissions from vehicles and human exposure to such pollutants have increased historically (World Health Organisation, 2016).

However, whilst the last few decades have seen consistent increases in road transport's contribution to air pollution, there are recent signs of progress and some positivity for the future.

In September 2015 the United States Environmental Protection Agency (EPA) gave a Notice of Violation of the Clean Air Act (CAA) to Volkswagen Group (VWG) stating that they had been using a device to circumvent the emissions tests on specific diesel engines between 2009 and 2015. Whilst the engines passed all the type approval tests, the laboratory results fell considerably short of measured real-world emissions in relation to gkm NOx limit values. As details of the scandal (also referred to as 'Dieselgate' in the media) became more public, it emerged that a 'cheat device' had been installed across a wide range of vehicles, not just limited to the United States of America (USA). It is estimated that the total number of vehicles affected by the scandal was approximately eleven million worldwide (Hotten, 2015).

The fall out of this scandal has been vast, extending far beyond the financial implication for VWG, whose share value dropped by approximately 40% at the peak of the scandal; and outstanding legal claims against VWG exceed three billion Euros. The scandal gave a voice to criticism of the standardisation of laboratory emissions tests throughout the worldwide automotive industry.

Whilst the use of a specific emissions cheat device was isolated to VWG, a number of significant inadequacies in the laboratory based tests used to regulate automotive emissions worldwide drew significant attention, including criticism of the New European Drive Cycle (NEDC) used in the UK and Europe. Both the testing process, such as the selection of new or well-maintained vehicles chosen for tests; and the type of fixed drive cycle testing was shown to be not necessarily representative of all vehicles on the road or real-world driving conditions (Li et al., 2014). Moreover, when compared to other vehicle marques it was identified that VWG vehicles were out-performing eight of the manufacturers analysed (Carslaw and Rhys-Tyler, 2013). Whilst previous studies had already identified these trends, the scandal gave attention to the findings (See Carslaw and Rhys Tyler, 2013; Carslaw et al., 2013; Carslaw et al., 2015).

It should be noted that this same criticism was not drawn against the results of The Common ARTEMIS Drive Cycle (CADC), the chassis dynamometer drive cycle developed by the ARTEMIS project; and used to build the IEM Analysis of Instantaneous Road Emissions (AIRE) used in this research (See Section 2.7.1).

Evidence suggests that demand for both new and used diesel vehicles has fallen markedly since the emissions scandal in September 2015, for example, diesel's share of the new UK car market reduced to 35% from 44.5% between 2016 and 2017 (Society of Motor Manufacturers and Traders, 2018). The longer term implication for diesel car sales is unknown, and direct evidence of a reduction of NO2 levels as a result of a reduction in the market share of diesel vehicles is difficult to quantify. However, if a reversed trend away from the dieselisation of UK and world vehicle fleets continues it is likely to provide a positive contribution and provides some hope that transport's contribution to poor air quality in our cities may diminish.

Moreover, the details of London's Ultra Low Emission Zone (ULEZ), due to come into force in April 2019, provide little doubt that diesel vehicles have been identified as a political target for change. The ULEZ specifically requires diesel cars to be Euro 6 compliant, in comparison to Euro 4 compliance for their petrol equivalent (TfL, 2018).

Considering the wider future air pollution from road transport there is considerable hope for favourable longer term improvement. Sales in hybrid and electric vehicles are at a critical stage with cumulative year-on-year uptake of such vehicles increasing from 20,000 in 2013 to more than 135,000 in 2017 (DfT, 2017). As a result the predictions for future vehicle fleets are likely to have a high margin of error, due to the level of uncertainty for continued future growth. Furthermore, given the increased rate of increase in uptake of electric vehicles in very recent years it could be argued that the decision to review transport strategies that exercise VKT restraint risks become obsolete, as policy may instead look to promote electric vehicles at the expense of modal shift. Future work to explore expansion of electric vehicles at the expense of VKT constraint should be completed. However, there is a vast body of work in support of the wider benefits of modal shift (Mullen et al, 2015); and the author hopes that policy supporting soft measures and other non-polluting models continues to prevail.

### 2.3 Air Pollution and health policy

A wealth of literature and comprehensive reviews of the health impacts of both regulated and unregulated air pollutants can be found and the impacts of pollution episodes on human health in the UK and across Europe are well documented (e.g. Anderson, 2009; Balmes et al., 2010; DEFRA, 2011; COMEAP, 2013; COMEAP, 2015). There is clear evidence of the adverse effects of outdoor air pollution, especially for cardio-respiratory mortality and morbidity (Kapposa et al., 2004; Barceló et al 2009). It is estimated that each year in the UK, short-term air pollution is associated with 50,000 premature deaths (EAC, 2010). In 2010 air pollution was estimated to reduce the life expectancy of every person in the UK by an average of 6 months (DEFRA, 2010a). A detailed breakdown on the impact of transport related air pollutants can be found in **Appendix A.**

Current action to manage and improve air quality is largely driven by European (EU) legislation. The 2008 Ambient Air Quality Directive (2008/50/EC) sets legally binding limits for concentrations in outdoor air of major air pollutants that impact public health such as particulate matter ($PM_{2.5}$ and $PM_{2.5}$) and nitrogen dioxide ($NO_2$). The 2008 directive replaced nearly all the previous EU air quality legislation and was made law in England through the Air Quality Standards Regulations 2010, which also incorporates the fourth air quality daughter directive (2004/107/EC) that sets targets for levels in outdoor air of certain toxic heavy metals and polycyclic aromatic hydrocarbons (DEFRA, 2011).

Legislation exists for emissions of air pollutants with the main legislation being the UNECE Gothenburg Protocol which sets national emission limits (ceilings) for Sulphur Dioxide ($SO_2$), NOx, Ammonia ($NH_3$) and VOCs for countries to meet from 2010 onwards. Similar ceilings have been set in European law under the 2001 National Emission Ceilings Directive (2001/81/EC), which was subsequently made into UK law as the National Emission Ceilings Regulations 2002 (DEFRA, 2011).

In the UK the Government is required under the Environment Act 1995 to produce a National Air Quality Strategy (NAQS) that contains standards, objectives and measures to improve air quality. At the local level, the Environment Act 1995 required local authorities to carry out a review of air quality, resulting in the regulatory regime Local Air Quality Management (LAQM). Since December 1997 each local authority in the UK has been carrying out a review and assessment of air quality in their area. Air pollution is measured and predictions have to be made on how it will change in the next few years. If a local authority finds any places where receptors are present (housing/ schools/ places of work etc.) where the objectives are not likely to be achieved, it must declare an Air Quality Management Area (AQMA) (Durham County Council, 2016). Then the local authority will put together a plan to improve the air quality - a Local Air Quality Action Plan (DEFRA, 2010b). The 'Local Air Quality Management Policy Guidance (PG16)' provides up to date statutory guidance for all relevant Local Authorities (both district and county level) regarding their obligations under the Environment Act 1995 (DEFRA, 2016).

Despite existing air quality legislation, EU countries (including the UK) are failing to meet targets, particularly for $NO_2$ (EAC, 2010). Political pressures for development and conflicts with short term economic objectives all impact on efforts to improve air quality. This reality comes despite guidance highlighting the economic benefit of improving air quality (DOH, 2010).

Given the overriding role of EU legislation in the UK's air policy, it is possible to suggest that there is potential for focus to shift away from the issue as a result of the UK's likely exit from the European Union. However, a review of UK air quality law suggests that there is limited risk of disruption given that even the UK's existing Air Quality Objectives are said to be at least as stringent as the limit values of the relevant EU Directives (Upton, 2017). Nonetheless there is potential for air quality targets to move away from meeting specific EU set air quality limit values, in favour of more objective regulation under the Air Quality (England) Regulations 2000.

Given that the UK has been in breach of the Air Quality Directive since 2010, it is also possible to speculate that the UK leaving the EU may avoid its obligations under the Directive, including the possibility of fines dependant on rulings from the ECJ. However, there is no certainty in this assumption. The current ongoing negotiations regarding the UK's likely exit from the European Union ensure that any resolute answers regarding the UK's future obligations are not possible. However, it has been reported that EU Environment Commissioner considers that the UK would still be liable to pay court fines handed down for offences committed when it was a member (Neslen, 2018).

## 2.4 Greenhouse Emissions and Climate Change

In 2014 the IPCC concluded that it is "extremely likely that more than half of the observed increase in global average surface temperature from 1951 to 2010 was caused by the anthropogenic increase in GHG concentrations" (IPCC, 2014) Human activity, including the burning of fossil fuels, land use change, and agriculture, has increased the concentration of GHGs in the earth's atmosphere (IPCC, 2014). $CO_2$ makes up almost eight percent of climate gases and is the most abundant greenhouse gas in the atmosphere (Pidwirny, 2006). The largest source of $CO_2$ emissions is from the natural processes of plant respiration, biomass decay and bacterial activity. In addition, $CO_2$ is emitted from a number of anthropogenic sources, namely transport, domestic and non-domestic sectors, agriculture and deforestation, industry (e.g. cement and metal production) and energy generation (DEFRA, 2011).

In the UK between 1990 and 2007 $CO_2$ emissions reductions were documented for the domestic (3.5 percent), power generation (11.5 percent), industry and agriculture (15 percent) and forestry sectors (17 percent) (DEFRA, 2010a). However, transport sector emissions increased by 18 percent between 1992 and 2004 (DEFRA, 2010a). Unfortunately the road transport sector has seen a continued increase in GHG emissions in recent history (IPCC, 2014). Consequently governing bodies across the globe are, through legislation, obligated to develop and implement strategies to reduce air pollution and GHG emissions from all sources including road transport, for example, the Kyoto Protocol (UNFCCC, 1998).

There is a complex and dynamic relationship between air quality and climate change pollutants. They can share common sources, and some air quality pollutants, such as ozone and particulate matter, have a direct effect on climate (DOH, 2010). Recent literature has highlighted the need for a combined approach to tackling both air quality and GHG emissions (DOH, 2010). Ms Isabel Dedring, London Mayoral Adviser on the Environment concluded that there was "not enough tied-up thinking" between the two issues (EAC, 2010). Limited research has been conducted on measuring the effect that action to reduce GHG emissions has on air quality. In addition, any implications for EJ have been largely ignored.

## 2.5 Environmental Justice

The term commonly used to express social equity in environmental legislation and policy is Environmental Justice (EJ) (Agyeman and Evans, 2004). Cutter (1995) defines EJ as equal access to a clean environment and equal protection from possible environmental harm irrespective of race, income, class, or any other differentiating feature of socio-economic status. Similarly, the UK Environmental Agency describe EJ as being "concerned with how environmental 'bads', such as pollution, and 'goods', such as access to green space, are distributed across society". It also considers the equity of environmental management intervention and public involvement in decision making. Correspondingly, Friends of the Earth Scotland define EJ as "… the idea that everyone has the right to a decent environment and a fair share of the Earth's resources" (cited in Walker, 2012). Furthermore, the US Environmental Protection Agency (EPA) defines EJ as the "fair treatment of all people with respect to environmental regulations and policies" (EPA, 1998). Fundamentally, the term is used widely to demonstrate a link within sustainable development between social justice and environmental issues. However, as Agyeman and Evans (2004) note, EJ is a contested concept with many possible definitions.

John Rawls (1971) suggested that justice is about fairness; that a just society is one in which everyone receives a 'fair' share of the available resources. However, there is much disagreement about what counts as 'fair' (Davoudi and Brooks, 2012). A full account of philosophical and political theories addressing this question is beyond the scope of this research, however, by way of summary a distinction can be made between strict egalitarian, libertarian, and utilitarian theories. Egalitarian equality (everyone should receive the same amount regardless of their input or need); libertarian equity (what people receive from society should be based on what they contribute to it); and utilitarian welfare (what people receive should be based on their need) (Buttram et al.„ 1995). Rawls's 'Difference Principle' supports a welfare approach, proposing that inequalities are justifiable if they are "to the greatest benefit of the least advantaged members of society" (citied in Buttram et al.„ 1995). This implies that in contemporary unequal societies, such as ours, the needs of disadvantaged people should be given priority (Davoudi and Brooks, 2012).

Discussion on how a libertarian approach of minimising government intervention and control over individual choices extends to fairness in air quality, and particularly in terms of government action on reducing air pollution is complex and potentially contradictory. Sovacool and Dworkin (2014) discuss energy subsidies, which receive funding from taxes, and are largely in place to ensure a 'cleaner' energy market. A libertarian could consider this an involuntary transfer of public money to chosen industries and producers. "To take this money for any reason, except to provide basic policing powers – the only legitimate governmental power, according to the libertarian – is to limit a person's rights and freedom" (Sovacool and Dworkin, 2014). Furthermore, the International energy agency suggests that removing energy subsidies in a group of eight developing economies would reduce energy use by 13 percent, and reduce carbon dioxide emissions by 16 percent (cited in Sovacool and Dworkin, 2014). Following this context of libertarian equality tacking air quality issues through market intervention would seem unjustified.

However, given that air pollution has a direct impact on health, a libertarian would also consider the problem as much an aggression as any other physically injury against an individual. The major function of government is to stop aggression; and the demonstration of injustice in air quality represents a failure to protect against air pollution. For example, Germani et al. (2014) find that greater judicial inefficiency (or lenient law enforcement) is associated with higher levels of pollution. In this analysis the government must act to tackle air pollution regardless of who is impacted or how much the individual has contributed to the issue.

It can be argued that, in general, in the UK a market oriented, libertarian approach exists to wealth and economy (Fecht et al., 2015). Discussing the impact of political attitudes on the EJ of air pollution Fecht et al. (2015) suggest that the historical social contract that exists in society may have bearing on current spatial distribution of air quality. In contrasting two countries, they describe the Netherlands as being driven by an egalitarian approach which strives to eliminate any form of inequality in society, whilst concluding that a more traditional class system present in the UK's housing market may contribute to the higher inequality observed in their findings when reviewing UK air pollution.

Discussing EJ in the UK, Mitchell and Dorling (2003) cites new European Community laws on enabling rights, driven by the 1998 Aarhus convention (United Nations ECE/CEP/43). The Aarhus convention aims to give substantive rights to all EU citizens on three principal environmental matters:

- Public access to environmental information
- Public participation in environmental decision making
- Access to justice in environmental matters

Directives on the first two matters are well advanced in the EU legislative process. The third concern has the objective of giving the public access to judicial and independent procedures to challenge acts or omissions by public authorities and private persons which contravene environmental laws (Mitchell and Dorling, 2003).

It is recognised that the term ‘EJ’ stems from the American Civil Rights movements in the early 1960’s (Agyeman and Evans, 2004 and 2005; Mitchell and Dorling, 2003; Mitchell et al., 2015; Chakraborty, 2017). In recent years the concept of EJ has been growing in significance. For example, in the USA, the analysis of EJ has been integrated into environmental and public health policy assessment. The National Environment Policy Act (NEPA) addresses EJ within the planning and decision-making process, defining ‘fair treatment’, as that where no group of people bear a disproportionate share of the environmental and adverse health impact of development (EPA, 1998).

However, in a UK context EJ is increasingly wrapped in the globalising cloak of human - rather than the Americanising one of civil - rights (Agyeman, 2012). More recently, the idea of EJ has been extended beyond environmental burdens to include environmental benefits (Fecht et al., 2015). Whilst the UK does not have an EJ movement to compare with that of the USA, interest in the field has grown in the last 15 years. Furthermore, this interest spans academics (Stevenson et al., 1998; Mitchell and Dorling, 2003; Agyeman and Evans, 2004; Agyeman, 2012; Mitchell et al., 2015); NGOs (Pye et al., 2006) and pressure groups (See Walker, 2012).

These activities have supported the strong policy guidance from the EU, leading government to voice strong support for the principle of EJ, although this has not yet been translated into significant activity at the regional and local levels (Mitchell and Dorling, 2003).

Current impact assessment methods and their implementation in the UK are failing to provide an effective analysis of EJ issues in policy making and project approval (Walker et al., 2005). Therefore there is considerable scope for developing more effective EJ orientated distributional analysis. It is known that the quality of our environment in the UK is improving as a result of emissions regulations across all sectors; despite this the scale of improvement can differ amongst varying community areas and pollution hot spots remain a concern (DOH, 2010). Nonetheless, new appraisal procedures for transport schemes do include an assessment of the impact on social equality as well as air quality (DfT, 2016).

### 2.5.1 **Deprivation and Health**

In order to understand links between deprivation, air quality and health it is important to consider the wider picture of social deprivation and health. Despite huge improvements in the health of people in England over the last 150 years, there are marked differences in the health of different groups (DOH, 2010). The most notable statistics for England relate to the life expectancy of different social groups; the higher an individual's social group, the longer he or she is likely to live. The presence of inequalities in mortality according to socio-economic position is well known, and has been the subject of a number of studies (DOH, 2010; Acheson, 1998). The Department of Health (DOH) (2010) strategic review of health inequalities concluded that a social gradient in health persists and that action should focus on reducing it. In England, the many people who are currently dying prematurely each year as a result of health inequalities would otherwise have enjoyed, cumulatively, between 1.3 and 2.5 million extra years of life (DOH, 2010). Inequalities in any aspect of life leads to poorer overall health for the population (Walsh et al., 2010). At the global scale since the adoption of Agenda 21 at the UN Conference on Environment and Development, attention has been drawn to understanding the links between health and the environment by policy makers.

After a review on health inequality the DOH concluded that 'social injustice is killing on a grand scale'. In England, people living in the poorest neighbourhoods, will, on average, die seven years earlier than people living in the richest neighbourhoods. Even more disturbing, the average difference in disability-free life expectancy is 17 years (DOH, 2010).

Action taken to reduce health inequalities can benefit society in many ways. Economic benefits would arise from reducing losses from illness associated with such inequalities. It is estimated that inequality in illness accounts for productivity losses of £31-33 billion per year, lost taxes and higher welfare payments in the range of £20-32 billion per year, and additional NHS healthcare in excess of £5.5 billion per year (DOH, 2010).

The Commission on Social Determinants of Health concluded that social inequalities in health arise because of inequalities in the conditions of daily life and the fundamental drivers that give rise to them: inequities in power, money and resources (CSDH, 2008). In summary, health inequalities result from social inequalities. Action on health inequalities requires action across all the social determinants of health. Focusing solely on the most disadvantaged will not reduce health inequalities sufficiently and in order to reduce the steepness of the social gradient in health, actions must be universal, but with a scale and intensity that is proportionate to the level of disadvantage. This is the concept of 'proportionate universalism' (DOH, 2010).

The term 'social deprivation' lacks a universally identified definition. Various UK indices of deprivation, for example, Indices of Multiple Deprivation (IMD) are discussed in Chapter 3. In the context of efforts to tackle health inequality in 2004 as a result of the Spending Review the government identified 'The Spearhead Group' for the purpose of monitoring Public Service Agreement (PSA) targets. The targets aim to see faster progress compared to the average in the "fifth of areas with the worst health and deprivation indicators". The Spearhead Group is made up of 70 Local authorities and 88 Primary Care Trusts, based upon the Local Authority areas that are in the bottom fifth nationally for 3 or more of the following 5 indicators: Male life expectancy at birth; Female life expectancy at birth; Cancer mortality rate in under 75s; Cardio Vascular Disease mortality rate in under 75s; and Index of Multiple Deprivation 2004 (Local Authority Summary) average score (Syed, 2006).

Of relevance to this research is the fact that a steeper socio-economic gradient in health exists in some regions than in others. The National Statistics Socio-economic Classification (NS-SEC) is an occupationally based classification but has rules to provide coverage of the whole adult population. Since 2001 the National Statistics Socio-economic Classification (NS-SEC) has been used for all official statistics and surveys. Figure 1 shows that the North East has a steeper gradient for life expectancy than the South West, showing socio-economic classification has more influence on mortality rate, providing potential evidence of greater injustice. In fact, the North East has the unfortunate credit of having both the highest mortality rate in the UK and the steepest life expectancy gradient (DOH, 2010).

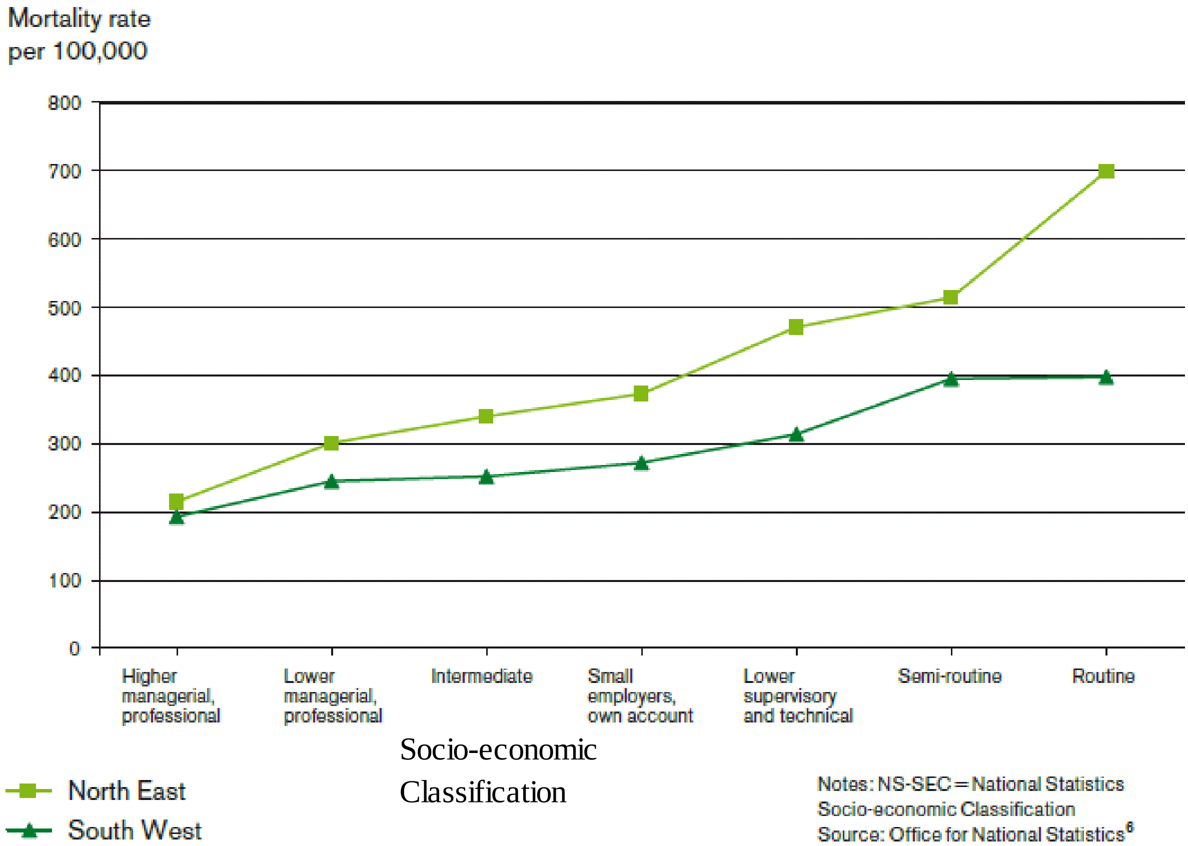


Figure 1. Age standardised mortality rates by socio-economic classification (NS-SEC) in the North East and South West regions, men aged 25-64, 2001-2003 (citied from (DOH, 2010)).

In 2010, the ONS reported that Mortality rates for the 'Routine' class declined on average by around 11 deaths per 100,000 population per year, almost double that of the 'Higher managerial and professional' class. Absolute differences between the mortality of the least and most advantaged classes showed a small decline based on three different measures. Relative differences, however, increased over this period. In 2001 the mortality rate of those in routine and manual occupations was 2.0 times that of those in managerial and professional occupations. In 2008 that ratio had risen to 2.3 (Langford and Johnson, 2010).

The Income Deprivation Affecting Children Index (IDACI) is a measure of the percentage of children (under 16) who live in income-deprived families. According to the Children's Index, Newcastle has 43 Super Output Areas (SOA) (out of 173) in the most deprived 10% of SOAs in England. The index illustrates Newcastle upon Tyne as a relatively deprived city. SOAs were designed to improve the reporting of small area statistics and are built up from groups of output areas (OA). Their boundaries can be downloaded from the 'Open Geography Portal' (Office of National Statistics, 2016). However, it remains important to note that children have become less deprived since the equivalent Index was produced in 2004, when 52 SOAs were in the 10% most deprived nationally (Office of National Statistics, 2016).

When assessing links between air quality and health it is clearly important to consider all drivers of health inequality. If a social gradient for air quality in the North East is identified in this research it must be considered against other social gradients that exist, from skills and education; employment; healthy standards of living and healthy and sustainable places (of which air quality has a bearing); and other social gradients in smoking, obesity, lack of physical activity and unhealthy nutrition. Failure to understand the wider issues in health, and other factors, for example, the 'Scottish effect', a term used to describe the higher levels of poor health experienced in Scotland over and above that explained by socio-economic circumstances, may lead to false conclusions and/or policy suggestions in this project (Walsh et al., 2010).

It is hoped establishing links between deprivation, air quality and health will increase the profile and visibility of air quality issues in the UK and across the world. This expectation contributes to the justification of this PhD research. However, it must be noted that it is not proposed to investigate the causal factors behind these links. The fundamental issue of resolving EJ (and thereby resolving underlying social issues) falls significantly beyond the scope of this project.

### 2.5.2 Environmental Justice and Air Quality

A link between deprivation and air quality has been established by a number of studies. Mitchell and Dorling (2003) completed a comprehensive review of UK air quality EJ studies and concluded that most research investigating the relationship between air quality and deprivation tended to show that air pollution is greater in more deprived communities (Mitchell and Dorling, 2003). Furthermore, a more recent update by Mitchell et al. (2015) looking at the EJ of UK air quality 2001-2011, found that improvement in the UK's air quality has been substantial but unequal, as whilst annual average $NO_2$ concentrations have fallen, the rate of improvement has been slower in more deprived areas. Additionally, for pollutants where concentrations continue to rise, such as $PM_{10}$, the rate of rise is highest for the poor.

Pye et al. (2010) conclude that "those living in the most deprived parts of England experience the worst air quality" and Walker et al., 2005 presents evidence that people in the most deprived ten percent of areas in England experience the worst air quality, and 41 percent higher concentrations of $NO_2$ from transport and industry than the average. This work does not consider the causes behind these findings or why these relationships should exist. Similarly, this research will not attempt to determine causal factors. Such a study would require the investigation of underlying social equity issues, the scope of which is considered too large due to the complexity of interlinking economic, social and environmental factors which act at all spatial scales. Nonetheless, the importance of incorporating EJ into wider environmental sustainability operations is acknowledged (Allu, 2016). Andrew Dobson's (cited in Mitchell et al. 2015) 'reluctant conclusion', that environmental sustainability and social justice are not always compatible objectives is also acknowledged, and supported by research on environmental justice and air quality assessments such as Mitchell et al. (2015).

As discussed in the introduction in Chapter 1 of this research, when analysing air quality and EJ it is also important to consider other factors that may be relevant to the relationship.

The majority of EJ and air quality studies focus on the health impact of environmental inequality (e.g. Walker, 2012; Mitchell et al, 2015; Unger and Bogaert, 2017). Air quality has been directly linked as a serious contributor to respiratory illness (Walker, 2012). However, as discussed the causes and environments that lead to respiratory illness are numerous, from early interactions between infectious agents such as viruses, bacterial infections, to an individual's composition of the respiratory microbiome (Unger and Bogaert, 2017).

It is therefore logical that, on an individual level, air quality may have only limited relevance to a particular respiratory illness. In combination with individual general health, lifestyle choices such as prevalence of smoking, the number of potential confounding factors of consideration is significantly beyond what could reasonably be expected to be explored; and the prevalence of suitable data is a substantial limitation should such work ever be attempted. However, it is important to consider this weakness in the design of larger population based research. The research refinement process for this work, particularly with regards the selection of statistical analysis better suited to the presence of confounding factors, is discussed in Section 3.3.

Similarly, the relevance of historic, pollution induced neighbourhood sorting is introduced also in Chapter 1. Heblich et al. (2016) analysed 10,000 industrial chimneys in 70 English cities around the year 1880 and used terrain and wind patterns to predict where their smoke would have drifted, and found evidence of pollution induced neighbourhood sorting. As discussed, in reality the patterns that lead to areas of 'poor' and 'wealthy' areas in our urban spaces is hugely complex and varied, with geography (rivers, topography), natural resources (industry) and land type (building) among many contributing factors which determine where people live and the relationship between air quality and EJ. Therefore, the presence of both historic and current factors place constraints on people's choice of where to live, as land values prices place sections of society in different spatial locations, and influences environmental justice for the urban poor (Onstad, 1997). In this wider context, the presence of more recent air quality issues, which are largely traffic driven (See Section 2.2), are unlikely to be the key driver, or a strong causal factor, which has led to the current observed patterns of injustice in the spatial distribution of air quality. Nonetheless, despite this complex relationship existing research has found that air quality is an environmental justice issue, with poorer neighbourhoods more likely to face greater pollution. Therefore, attempts to understand and plan for scenarios which lessen or resolve the issue are nonetheless valid.

A minority of more recent environmental justice papers use a broader, more integrated, multilevel approach in order to enhance our understanding of environmental inequalities and the related health effects in an attempt to address some of the above limitations (Fecht et al., 2015). Conceptual papers have examined the role of structural drivers, social, economic, and political mechanisms, in the production of environmental inequalities (e.g. Solar and Urwin, 2010). Similarly, attempts have been made to analyse the role of health related behaviour or lifestyle as a mediation between the environment and health inequalities, including diet, physical activity, smoking and alcohol consumption. (Cutts et al, 2009).

However, whilst it is possible to strive for a holistic approach to wider EJ analysis, the conceptual analysis literature is met with the limitation that more empirical research is needed, as the individual interactions between determinants, such as air quality, and geography as still not accurately understood, requiring longitudinal environmental, health, and socio-demographic data (Fecht et al., 2015).

### 2.5.3 **Environmental Justice Studies**

As discussed in Section 2.5.2 Mitchell and Dorling (2003) and Mitchell et al (2015) completed a comprehensive review of UK air quality EJ studies which can be seen in Table 1. Furthermore, Bowen (2002) reviewed 42 EJ studies conducted in the USA since the early 1970s. This section makes reference to such reviews and provides an updated review of air quality EJ studies identified from the literature including a more global look at the present state of air quality EJ analysis. When considering EJ studies, an important consideration is the methodology adapted and the indicators used. Further to the discussion in Section 2.5 on what constitutes EJ, it is vital to understand that deprivation is not automatically the most appropriate demographic measure against which to assess environmental inequity (Mitchell et al., 2015; Andradea et al.; 2017). For example, as discussed by Mitchell et al. (2015), Stevenson et al., (1998) demonstrated a strong inequity in London air quality, with pollution highest in areas of low car-ownership. Moreover, more recently Rivas et al. (2017) demonstrated inequalities among different socio-economic groups in exposure to air pollutants during commuting in London.

Table 1 Air quality social equity studies (Adapted and expanded from Mitchell et al (2015).

| **Socioeconomic Indicator** | **Location** | **Observed association with socio-economic indicator** | **Reference** |
|---|---|---|---|
| Poverty | | | |
| Income; car ownership | Wards in Greater London, UK | Positive association between deprivation and $NO_2$ and respiratory diseases | Stevenson et al., . (1998) |
| Social class index | Local authority districts, UK | Weak positive association with $PM_{2.5}$ and $SO_2$ ; very weak positive association with $NO_2$ . Negative association with $NO_2$ and $SO_2$ when population density accounted for. | McLeod et al., (2000) |
| Index of multiple deprivation | Wards in five cities, UK | Weak positive association with $NO_2$ and $PM_{2.5}$ in three cities, inverse in two | King and Stedman (2000) |
| Index of multiple deprivation | Qards in Bradford, UK | Mapped data suggest that $NO_2$ and $PM_{2.5}$ ``tends to be highest in the most deprived areas". | Pennycook et al., (2001) |
| Index of multiple deprivation | wards in London, Birmingham, Belfast, and Cardiff, UK | Weak positive association with $NO_2$ and $PM_{2.5}$ in all cities except Cardiff. | Pye et al., (2001) |
| Various indexes | Enumeration districts in Birmingham, UK | Strong positive relationship with poverty, but | Brainard et al., (2002) |

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| | | difficult to separate effect from ethnicity. | |
| Social class | West Glamorgan, Wales | No association with $NO_2$ , but analysis of small sample (171 adults). | Lyons et al., (2002) |
| Townsend index | Leeds, UK (3600 point observations) | Strong positive correlation with $NO_2$ . | Mitchell (2002) |
| Breadline Britain index | All census wards in Britain | No association with $NO_2$ or CO emission for any age group Poorest wards emit least NOx from resident vehicles but have highest $NO_2$ exposure $NO_2$ 40–80% above mean for young children and 18–40 yr olds, reflecting urban to rural life stage migration | Mitchell and Dorling (2003) |
| Carstairs deprivation index | England and Wales | Environmental inequity in England and Wales. associations are dependent on the environmental and deprivation measures under consideration | Wheeler (2004) |
| Household income | Hamilton, Canada | Differences in exposure to air pollution accounted for some of the socio-economic differences in circulatory disease (cardiovascular and stroke) mortality | Finkelstein et al., (2005) |
| College education, monthly income, and housing | Six regions in Sa˜o Paulo, Brazil | Socio-economic deprivation represents an effect modifier of the association between | Martins et al., (2005) |

| | | | |
|---|---|---|---|
| | | air pollution and respiratory deaths. | |
| Townsend index Non car ownership | Leeds, UK | Inequity in residential $NO_2$ concentration in Leeds does occur Likely to contribute to above average respiratory disease burden in deprived communities | Mitchell (2005) |
| Multiple demographic and socio-economic variables | Christchurch, New Zealand | Levels of pollution are higher in more deprived communities. Deprived communities are exposed to a greater proportion of extreme pollution events | Pearce et al., (2006) |
| Index of multiple deprivation (Variations in analysis scale, deprivation measures) | LSOAs, UK | Inequalities in the distribution of pollutant concentrations for $NO_2$ and $PM_{2.5}$, and for $SO_2$ in England and Northern Ireland. | Pye et al., (2006) |
| Census, educational, and death registries | Oslo, Sweden | PM2.5 was associated with most neighbourhood-level indicators of deprivation, as was most clearly seen for type of dwelling and ownership of dwelling. | Ness et al., (2007) |
| New Zealand census (income)/ New Zealand Deprivation Index | Christchurch, New Zealand | Mean exposure to pollution is highest in the most disadvantaged areas of the city. Furthermore, areas where car ownership levels are highest tend to have relatively low levels of pollution exposure. | Kingham et al., (2007) |
| British Household | UK (longitudinal | Strong evidence for | Jones and Wildman |

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|---|---|---|---|
| Panel Survey | sample of over 5000 households, containing over 10,000 adult individuals) | the impact of income on self-reported measures of health for men and women | (2008) |
| Cumulative deprivation index (CDI) and Cumulative Health Index (CHI) | Leeds, UK | Positive but weak relationship exists between air quality and social deprivation, and indicates that deprived population groups are disproportionately exposed to higher $NO_2$ levels. | Namdeo and Stringer (2008) |
| Urban area gross domestic product | 22 provinces in China, where more than 85% of the national population reside | Elderly residents living in areas with a higher gross domestic product (GDP) were more susceptible to the effects of air pollution than those living in low GDP areas | Sun and Gu (2008) |
| Dwelling value, Low income, Unemployment rate | Hamilton, Canada | Groups with lower socio-economic status are exposed to higher levels of ambient particulate air pollution | Jerrett et al., (2009) |
| Carstairs Index (plus additional variables) | Leicester, UK | Relationship between children's hospitalisation rates and socio-economic-status, ethnic minorities, and $PM_{2.5}$ road-transport emissions within Leicester. Affluent intra-urban communities contribute the highest levels of emission, while residentially experiencing relatively low exposure of | Jephcote and Chen (2011) Jephcote and Chen (2012) Jephcote and Chen (2013) |

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|---|---|---|---|
| | | transport emissions. | |
| Area deprivation | Urban parts of New Zealand for Which particulate air pollution data were available | Socio-economic inequalities in respiratory disease mortality were not significantly elevated with $PM_{2.5}$ exposure. | Richardson, 2011 |
| Census demographic data, 2000 Census Block Group (BG) | US regions, states, counties and urban areas. | Inequality and injustice metrics vary by location. Non-white ethnic groups experience higher residential outdoor $NO_2$ concentrations than whites. | Clark et al., 2014 |
| Social categories and gender composition. | Italy, by provinces | Pollution releases increase with income (then follow an inverse U-shaped environmental Kuznets curve); releases tend to be higher in provinces with high concentration of females as households' head and with high concentration of children; and greater judicial inefficiency (or lenient law enforcement) is associated with higher levels of pollution. | Germani et al., 2014 |
| 2011 census from the Australian Bureau of Statistics (ABS Statistical Area Level 1 (SA1)) | Major urban areas in Australia | Environmental inequalities in ambient $NO_2$ levels in the major urban areas of Australia between Indigenous and non-Indigenous persons. | Knibbs and Barnett, 2015 |
| "Socio-economic Atlas 2006" prepared by the Metropolitan Regional | Santiago, Chile | The areas of the Santiago metropolitan region with the worst air quality have lower | Rose- Pérez, 2015 |

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| government. | | socio-economic levels. Pollution in these areas reaches levels higher than the current Chilean 24 hour standard for fine particles. These areas also have longer time periods of unhealthy air and 21 % more days with unhealthy levels of air pollution. | |
| Geographically-based health survey and neighbourhood characteristics | Hartford, UK | The effects of a given pollution level tend to be more serious for specific subgroups based upon sex, ethnicity, poverty, and age. | Stewart et al, 2015 |
| Townsend index | UK | Improvements in GB's air quality has been substantial but unequal. Annual average $NO_2$ concentrations have fallen, but the rate of improvement has been slower for the more deprived. Conversely annual average PM10 concentrations have risen, and done so more quickly for the poor. | Mitchell et al, 2015 |
| IMD and 2011 Census Special Workplace Statistics | London, UK | The most deprived income group showed the overall highest concentrations of all PM fractions. | Rivas et al., 2017 |
| Ethnicity | | | |
| Ethnicity Percentage of household heads from India and New Commonwealth | Local authority districts, UK | Positive association with $NO_2$, $SO_2$ and $PM_{2.5}$ , not attributed to multicollinearity with deprivation | McLeod et al., (2000) |

| | | | |
|---|---|---|---|
| | | measure. | |
| Percentage of self-reporting as white, Asian, or black | Enumeration districts in Birmingham, UK | Strong positive relationship with ethnicity but difficult to separate effect from poverty. | Brainard et al., (2002) |
| Demographic and socio-economic variables extracted from Census 2000 at the census tract level | Florida, USA | Race and ethnicity are significantly related to cancer risks in Florida, | Gilbert and Chakraborty (2010) |
| Age | | | |
| Pensioners , >60, < >65 years; <15 years | Enumeration districts in Birmingham, UK | No association with $NO_2$ or CO emission for any age group. | Brainard et al., (2002) |
| Time use surveys | Germany and UK | Age and gender at least as important in identifying EJ in urban areas as are income, education and employment situation. | Gaffron (2011) |

An overarching conclusion from the review of findings in EJ literature would suggest that strong socio-environmental inequalities prevail throughout modern society. Poverty status may also involve increased susceptibility to environmental challenges by virtue of differences in underlying health status and access to medical care. For example, higher hospital admission-pollution risks were seen from patients described as meeting US poverty criteria (Walker, 2012). These relationships are complex due to variation in sensitivity to exposure, age, pre-existing health conditions accumulative and synergistic effects 'double/triple jeopardy' for vulnerable populations; poor socio-economic conditions interact with both poor health and a poor living environment (World Health Organisation, 2016; Ma et al., 2016).

A key factor of consideration identified during the review of EJ studies was scale, or resolution at which the socio-economic characteristics are measured (Clark et al., 2014; Norman, 2016; Fernándeza and Wua, 2017). Finer measures of socio-economic status (e.g. individual-level or small geographical areas) have tended to find that socio-economic characteristics modify the relationship between air pollution and mortality (Walker, 2012).

Both Stevenson et al., (1998); and Mitchell and Dorling (2003) conclude that since the mid-nineties transport is the main contributor to poor air quality in Air Quality Management Areas, and the main cause of respiratory illness and deaths amongst vulnerable groups such as young children.

Moreover, as previously discussed, the updated research by Mitchell (2015) has shown that whilst improvement in the UK's air quality has been substantial, it has also been unequal in the decade since 2001. Annual average $NO_2$ concentrations have fallen markedly, but the rate of improvement has been slower for the more deprived (Mitchell et al., 2015). Additionally, annual average $PM_{10}$ concentrations have risen, and done so more quickly, for the poor (Mitchell et al., 2015).

## 2.6 Emissions Factor Collection Methods

An accurate assessment of the level of air quality is a vital requirement for authorities to be able to develop new policies and strategies. The ability to identify those areas within a city or region that do not meet air quality standards is paramount if such policies are to be successful. In an ideal world pollution concentrations would be continuously measured and monitored everywhere throughout a conurbation. In reality this is neither physically or financially feasible (Smit et al., 2010). Instead policy makers must rely on air quality models (atmospheric dispersion models fed by emissions models) to predict the spatial distribution of pollutants over a given area.

The calculation of road traffic emissions involves combining traffic data (e.g. distance travelled and speed) with details of the vehicle fleet (vehicle type, size, engine size, fuel type, Euro emissions standard, age and exhaust treatment technology) and emissions factors (g/km) (Barlow and Boultier, 2009; Boultier et al., 2012). The National Atmospheric Emissions Inventory (NAEI) defines an emissions factor as the "relationship between the amount of pollution produced and the number of vehicle miles travelled" (NAEI, 2012b).

Emissions models allow the emissions from a given geographical area including a stretch of road or road network to be estimated (e.g. Kassomenos et al.,2006; Kyle and Kim, 2011; Boultier et al., 2012). These estimates can be compiled using an emissions model to create an emissions inventory (NAEI, 2012a). A number of emissions modelling approaches have been developed. For example, average-speed, corrected average-speed, traffic situation, multiple linear regression and instantaneous models (Highways Agency, 2015).

Given that emissions models are typically represented by emissions factors and emission factors are in turn dependent on several other factors (such as type of fuel, type of engine, age of the vehicle, driving cycle etc.) it is first necessary to document the methods by which emissions factors are developed (Cairns, 2013; Franco et al., 2013).

Some alternatives to dynamometer experiments include on-board measurements (e.g. Huo., 2012) and remote sensing measurement (e.g. Guo and Zhang, 2007). It is these approaches that are the focus of the following sections. Other methods to estimate road emissions, such as tunnel experiments, inverse modelling, and mass balance are less commonly adopted (Cairns, 2013).

### 2.6.1 **Dynamometer Tests**

Dynamometer emissions estimates are calculated by running a vehicle on a dynamometer under controlled conditions (Barlow and Boultier, 2009). Vehicle exhaust gases are simultaneously collected and subsequently quantified to provide emissions estimates (Carnes, 2013). The dynamometer test is the most widely used method of estimating emissions from road vehicles (Joumard et al., 2000). The vehicles are subjected to various driving cycles, which include changing the dynamics of the vehicle to reflect 'real world' driving conditions (Andre et al., 2006; Kamble et al., 2009).

The primary advantage of dynamometer for recording emissions factors is that the tests are carried out in a controlled laboratory environment, ensuring the test procedures can be easily reproduced (Barlow and Boultier, 2009; Cairns, 2013). Current driving cycles are created using on-road driving data (e.g. ARTEMIS; Assessment and Reliability of Transport Emissions Models and Inventory Systems) rather than simulation methods (Kamble et al., 2009).

However, the dynamometer (or driving) cycle is widely accepted as a major limitation of laboratory based emissions testing (See Jenkin et al., 2008; Carslaw et al., 2011). Variances are noted between the represented outputs of laboratory dynamometer driving cycles and on-road real world driving conditions (Joumard et al., 1999; Andre et al., 2006; Smit et al., 2010; Grieshop et al., 2012). The most widely accepted cause of these variances concerns the application of emissions factors developed from generic, or 'standard' driving cycles (e.g. Joumard et al., 1999; Kamble et al., 2009).

These cycles are typically the legislative cycles used for testing vehicles registered within a country or region (e.g. Europe). Emissions factors developed from these standard driving cycles have been shown to substantially underestimate emissions (e.g. Carslaw et al., 2011; Joumard et al., 2000). The majority of these underestimation discrepancies have been identified as being due to the inability of standard cycles to take into account the more aggressive acceleration behaviour that present at a local level (Durbin et al., 2002). However, the development of local cycles is expensive and impractical, ensuring 'standard' driving cycles remain the only current practical solution (Cairns, 2013).

One of the most significant disadvantages of dynamometer tests is that road gradients can only be accounted for by varying engine load (Franco et al., 2013). The impact of road gradient is discussed in Section 2.7.1. Additionally, other 'real world' variations such as ambient temperatures are poorly reflected. Finally, the sampling factors affect the accurate representation of vehicle fleets. For example, accuracy is dependent on the number of vehicles tested, and the absence of gross emitters (often poorly maintained vehicles; catalytically convert failures etc.) may also lead to emissions underestimations (Carslaw et al., 2015).

### 2.6.2 **Instrumented Vehicles**

Instrumented vehicles calculate emissions factors by measuring the rate of emissions using on-board devices. Other relevant parameters (e.g. engine load, gear change etc.) are also recorded whilst the vehicle in is operation in real world conditions (e.g. Lenaers, 1996; Chen and Yu, 2007).

As the emissions are collected under real world conditions, external variables are accurately reflected in emissions estimates (Chen and Yu, 2007). Therefore, the measurements collected are regarded as being more representative of real world driving conditions than other, laboratory based methods (Chen and Yu, 2007).

Some significant disadvantages of the instrumented vehicle approach are the effect of route choice and restricted sample size. These two factors produce outputs which are directly representative of the local environment but which may not be applicable to wider geography or vehicle fleets (Carslaw et al., 2011).

### 2.6.3 **Remote Sensing**

Remote sensing detectors (RSD) pass ultraviolet and infrared beams of light through a vehicle exhaust plume; as the light is absorbed by its constituent gases and particles, emissions estimates are produced (Guo and Zhang, 2007).

RSDs can be used on the road side enabling large samples of vehicles driving in real world conditions to be gathered. Sample sizes from single research projects can be in the tens of thousands (e.g. Carslaw et al., 2011). The resultant large emissions factor databases ensure accuracy across large vehicle fleets. Such comprehensive databases have highlighted the discrepancies between dynamometer based emissions factors and real world conditions (e.g. Smit et al., 2010; Carslaw et al., 2011). Rhys-Tyler et al. (2011) concluded that RSD derived emissions allow for the variability of individual driver behaviour, and interactions with other road users and highway infrastructure to be accounted for when determining emissions factors.

However, there are significant drawbacks to using RSDs for calculating emission factors as they require daily multi-point calibration (Carslaw et al., 2011). The results are susceptible to local meteorological conditions, and there are current limitations on capturing vehicle emissions emitted from exhausts at varying heights (e.g. cars and HGVs are difficult to sample simultaneously) (Carslaw et al., 2011). Additionally, local road conditions and types affect results (i.e. gradient, number of lanes, urban environments) (Wyatt et al, 2014).

## 2.7 Emissions Models

A wealth of emissions models of varying complexity have been developed over the past 20 years. The role of emissions models in air quality modelling is to apply emission factors to generate emissions predictions. It should be noted that these models are greatly influenced by the emissions factors they comprise (Cairns, 2013).

Typically, emissions models used for air quality models rely on average speed based emission factors. The average speed and average flow of traffic on each road/link in a network is used in conjunction with a suitable emissions factor to calculate emissions estimates for the specific road/link. Outputs are provided based upon the principle that the average emissions for a certain pollutant and a given type of vehicle varies according to the average-speed during a trip (Barlow and Boultier, 2009). Therefore, a reasonable estimate of total emissions over an area can be given (Smit et al., 2010). This method is often adopted as the data requirements are often readily available (Barlow and Boultier, 2009). Their widespread use is ensured as they represent the traditional approach, they are comparatively easy to use, and their model input format is reasonably close to that of the data generally available to users (Boultier et al., 2007).

Examples of average speed based models include MOBILE (EPA), EMFAC (California Air Resources Board), COPERT (Ahlvik et al., 1997), PITHEM, (Namdeo et al 2002), and the average speed approach is exemplified by the model incorporated within the UK Design Manual for Roads and Bridges (DMRB). For example, PITHEM contains an integral emission model which calculates emissions and particulates using latest UK emission factors (i.e. National Atmospheric Emissions Inventory (NAEI)). National fleet emissions factors are determined as a function of vehicle type, age, emission control standard, engine size and fuel used. These factors are applied via PITHEM to 24 hour traffic count and traffic speed data obtained for each link in a given network. PITHEM is currently under development to take in to account updated NOx Emission Factors taken from the latest DEFRA Emission Factor Toolkit - Version 5.1.3.

However, it is recognised that average-speed emissions methods lead to significant underestimation of emissions on particular streets and junctions where congestion and queues build and prevail for a high proportion of the day (Boultier et al., 2007). A key cause of this underestimation is that trips with very different vehicle dynamics and emissions can have the same average-speed (Barlow and Boultier, 2009). For example, an average-speed of 60km/h on an arterial road could represent uncongested free-flowing conditions, whereas the same speed on a motorway would represent more congested conditions (Cairns, 2013). The presence of congested, stop-start conditions during a vehicle trip is of principle importance to the total emissions generated (Huo, 2012). Such conditions result in very short, sharp increases in emissions (Grieshop et al., 2012).

Average-speed average-flow emission factors for road vehicles are widely applied in regional and national inventories, and are currently used in a large proportion of local air pollution prediction models. However, limitations associated with the average speed average flow approach for this purpose also are recognised in the literature. These limitations are discussed in detail by Boultier et al. (2007) and include: the use of after-treatment devices causing emissions to be released as short, sharp peaks, often occurring during gear changes and periods of high acceleration, reducing the reliability of average speed as an emissions estimation tool; failings in the representation of real-world driving conditions; and the low spatial resolution of average speed models presenting a significant drawback when using emissions estimates to inform dispersion modelling.

Several studies have concluded that emissions should be described in terms of engine speed, load and power not just relating to vehicle speed (Shaw, 2015).

In recent years significant emphasis has been placed on the estimation of NOx emissions from road vehicles (Jenkin et al., 2008; Carslaw et al., 2011; Rhys-Tyler et al., 2011; Cairns, 2013; Carslaw et al., 2015). This is because of the majority of the UK's AQMAs are declared based on exceedances in $NO_2$ concentrations, despite emissions standards set in the UK which show a significant decrease in NOx emissions from road transport (Mitchell and Dorling, 2003; Chatterton et al., 2008).

The principle cause of increasing $NO_2$ concentrations despite cited reductions in emissions standards is an increase in the proportion of NOx emitted as f-$NO_2$ in vehicle exhaust fumes (Carslaw et al., 2015). This increase in f-$NO_2$ is due to increased proportion of diesel vehicles in the UK fleet as well as modern treatment technologies such as diesel particulate filters (DPF) (Jenkin et al., 2008). Other reasons for the failure to reduce $NO_2$ concentrations include higher real world catalyst failure and emissions degradation rates than estimated in the emissions standards, and inadequate test cycles which fail to reflect read world driving conditions (Carslaw et al., 2011).

### 2.7.1 **Instantaneous Emissions Models**

Instantaneous Emissions Models (IEMs) aim to address some of the limitations of average speed based models (Boultier et al., 2007). The benefits of instantaneous emission models include: their inherent ability to take into account the dynamic nature of driving cycles and the variability in emissions associated with given average speeds; the ability for user defined fleet profiles to be specified; and detailed spatial resolution outputs enabling significant improvement in the prediction of air pollution (Boultier et al., 2007).

Instantaneous emissions models methods have been explored for a number of years (e.g. Journard et al., 1995; Ahlvik et al., 1997; Shaw, 2015). These methods rely on an information database which enables the volume of a specific emission type to be derived for a given set of instantaneous operational characteristics for each vehicle. The database will typically provide information for differing vehicle types and engine sizes to enable variations in the vehicle fleet to be reflected (SIAS, 2012). Thereby, the volume of emissions that would be produced by a specified vehicle travelling at a given speed and rate of acceleration can be estimated. An emissions rate is calculated for each time period and the sum of all the time period rates is used as the overall link emissions value (Barlow and Boultier, 2009).

In a review of IEMs by Boultier et al. (2007) the type of IEMs are split in to three distinct categories (Figure 2).

| | |
|---|---|
| Unadjusted models (speed, acceleration) | MODEM (original version)<br>MODEM (extended version)<br>DGV |
| Unadjusted models (engine power) | PHEM (HDV part)<br>VeTESS<br>CHEM |
| Adjusted models | EMPA model<br>PHEM (PC part) |

Figure 2. Categorisation of IEMs.

The simplest types of IEMs define emissions and fuel consumption rates for different combinations of instantaneous speed and acceleration, usually in a matrix of bin ranges (Boultier et al., 2007; Ropkins et al., 2007). Other models have used factors of speed and acceleration instead of the acceleration rate alone (e.g. Joumard et al., 1995). Two examples of European IEM models are DGV (Digitised Graz model) and Modelling of emissions and fuel consumption in urban areas (MODEM) (Joumard et al., 1995). MODEM was first created during the European Commission’s DRIVE program. The database for the model was developed from laboratory emission test data collected by various European laboratories, with an additional set of emission factors later developed by the Transport Research Laboratory (TRL). Finally, a matrix with a finer resolution was developed for the extended version of MODEM (Boultier et al., 2007). However, various sources of error in the unadjusted instantaneous modelling approach have been acknowledged (Zhu and Ferreira, 2013). Examples of these errors include the types of drive cycle used; differences in the calculations of acceleration values; the grid size in the emissions matrix; and the type of interpolation scheme (Boultier et al., 2007).

The Assessment and Reliability of Transport Emission Models and Inventory Systems (ARTEMIS) project provided key understanding into the emission behaviour of modern vehicles. The aim of the project was to produce an emission model for road, rail, air and ship transport to provide consistent emission estimates at the national, international and regional level (Boultier et al., 2007). Thereby, one of the main aims of ARTEMIS was to develop a model capable of modelling emissions for all types of vehicle under a variety of conditions. The resulting tool was Passenger car and Heavy Duty Emissions Model (PHEM). PHEM can be regarded as an 'adjusted' model as the passenger car part of the model includes a signal adjustment (Boultier et al., 2007). However, the HDV part of PHEM does not include adjustments for the distortion of the emissions signal during measurement (Boultier et al., 2007). PHEM has been developed by the Technical University (TU) of Graz. PHEM is regarded as a powerful tool in emissions modeling and good accuracy is reached for most exhaust gas components (e.g. Boultier et al., 2007; Carslaw et al., 2012; Hirschmann et al., 2010; Anya et al., 2014).

PHEM is a vehicle dynamics model using 'engine power' maps. Emissions are calculated based on the instantaneous engine power demand and normalised engine speed during a driving pattern specified by the user (Boultier et al., 2007). From the input vehicle specification and speed (e.g. tyre size, gear ratio, weight, drag, etc.) PHEM determines the load on the engine, the engine speed and then the emissions (SIAS, 2012). Furthermore, TRL created IEM tables (similar to those in MODEM) by feeding drive cycle information into PHEM and then analysing the results. These detailed tables enable PHEM to provide information on a wider range of engines (From emissions EU standards 0 to 6), including a wide range of heavy vehicles (HGV's/ buses). Finally, the effects of vehicle load and gradient can be modelled by disaggregation of engine load data and subsequent emissions outputs. Another key advantage of the PHEM based approach to emissions modelling is that detailed outputs from a microsimulation model can be used to produce a more refined estimate of vehicle emissions (Carslaw et al., 2012; Grote et al., 2016).

AIRE (Analysis of Instantaneous Road Emissions) is an IEM designed to process the outputs from traffic microsimulation models (SIAS, 2012). AIRE has been developed by SIAS Limited (SIAS) in collaboration with TRL. The software development was undertaken by SIAS with the calculated outputs from the program independently verified by TRL. Following this verification, further testing was undertaken making use of modelled and observed vehicle trace data. Emissions estimates from AIRE were also independently compared against those obtained by traditional, average speed-based methods using real project examples (SIAS, 2012).

The basis for the development of AIRE is the underlying database of emissions factors (by engine size, fuel type, vehicle type, emissions standard, gradient level, etc.). This information was derived by TRL using the PHEM model developed by TU Graz (SIAS, 2012). To create a series of IEM tables, observed trace data from TRL drive cycles was fed into PHEM. These outputs were then collated and processed enabling the emissions to be established for each vehicle at a given speed and acceleration rate. Due to the large database and level of disaggregation in PHEM a total of 3129 IEM tables were created for use in the module (Shaw, 2015). For comparison, this compares with 40 – 50 IEM tables in the original MODEM model (Boultier et al., 2007).

AIRE can be used in conjunction with the outputs from any traffic microsimulation model, although it was specifically developed for use with S-Paramics (SIAS, 2012). Additionally, it could be used with driving patterns generated by GPS tracking of vehicles (SIAS, 2012; Gastaldi at al., 2014; Shaw, 2015). The module works by interrogating an output file called carpositions.csv which automatically produces the relevant output data required by the module including the vehicle type, speed, acceleration and gradient of each vehicle for every simulated timestep (0.5 seconds) (SIAS, 2012). Additional information including the network link, the grid co-ordinates and a unique vehicle tag is also produced to ensure that the outputs can also be examined on a link by link, vehicle by vehicle or on a geographical basis.

The IEM tables within the AIRE module provide the emissions factors used in the program. However, additional information is required to ensure that the vehicle fleet is accurately represented. AIRE adopts vehicle fleet projections from the NAEI and HGV proportions from the Department for Transport (SIAS, 2012). However, in order to take account of the latest fleet projections it is possible to adjust the vehicle fleet projections using the vehicle fleet spreadsheet within the AIRE module. For this research adjustments were made so as to best match the latest NAEI vehicle fleet projections (COPERT 4v8.1).

AIRE produces outputs for three emission types; Oxides of Nitrogen (NOx); Particulate Matter (PM); and Total Carbon. This information can be output from the post-processor module for each vehicle individually (output as timestep emissions values or summary values for the whole vehicle trip). Emissions can be output for the entire modelled network or for a subset of links in the network thereby providing a great deal of flexibility for the user in terms of the outputs and their subsequent analysis (SIAS, 2012).

Similar modules are also available linking PHEM outputs with other microsimulation packages; for example, Hirschmann et al. (2010) created a toolbox linking PHEM with VISSIM; and VISSIM to MOVES (Abou-Senna and Radwan, 2013); and VISSIM to EnViVer Pro (Eijk et al., 2013). However, the author deemed AIRE to be the most appropriate tool for this research as it was developed specifically for use with Paramics, and has been subject to more stringent checks. For example, calculated outputs from the program were independently verified by TRL, and following this verification further testing was undertaken making use of modelled and observed vehicle trace data (SIAS, 2012). Emissions estimates from AIRE were also independently compared against those obtained by traditional, average speed-based methods using real project examples (SIAS, 2012).

### 2.7.2 **Validation of Emissions Models**

Smit et al. (2010) highlighted that there was a lack of literature concerning emissions model validation. Testing the accuracy of road traffic emissions models is problematic, as real world emissions values are unknown and it is neither financially or practically viable to measure fleet wide emissions values (Cairns, 2013). Nonetheless it is important that attempts are made to validate emissions models so their accuracy can be estimated.

Some of the modelling methodologies discussed in Section 2.6 can also be used to validate emissions models. Examples of validation using instrumented vehicles (e.g. Joumard et al., 1995) and remote sensing (Carslaw et al., 2011) are typical of attempts to evaluate emissions models. The advantages and disadvantages of these techniques are one and the same as those considered and discussed in relation to methods for creating emissions inventories.

The alternative approach to validating emissions inventories is to use air quality concentration measurements (Cairns, 2013). This involves using emissions outputs in conjunction with an air quality model. Predicted pollutant concentrations can be compared with observed data allowing the accuracy of the emissions model to be assessed. Whilst this method has limitations, principally the accuracy of the air quality model, the technique is widely used and remains the most feasible methodology for emissions modelling validation due to the relatively low cost, and short timescales in which the assessments can be performed. For example, Taghavi et al., (2005) used the Regional Atmospheric Modelling System (RAMS) to evaluate two emissions inventories compiled over southern France (Cairns, 2013).

## 2.8 Atmospheric Dispersion Modelling

Air quality models are regularly used by UK local authorities for pollutant concentration forecasting and the review and assessment of air quality levels (Namdeo and Stringer, 2008). An accurate assessment of the level of air quality is a vital requirement for authorities to be able to develop new policies and strategies. As discussed in Section 2.6 the ability to identify those areas within a city or region that do not meet air quality standards is paramount if such policies are to be successful.

A wide variety and type of dispersion models have been developed for the purpose of air quality modelling. Examples of these can be found in Table 2 Common dispersion models (Adapted from Cairns, 2013)..

Table 2 Common dispersion models (Adapted from Cairns, 2013).

| **Model Type** | **Example** |
|---|---|
| Statistical | Stedman et al., 2001 |
| Numerical | HIWAY series; Zimmerman and Thompson,1975 |
| Receptor | COPREM; Wahlin, 2003 |
| Box | STREET BOX; Johnson et al., 1973 |
| Street canyon | OSPM; Hertel and Berkowicz, 1989) |
| Microscale CFD | (e.g. FLUENT; www.Fluent.com), |
| Urban scale | MEMO; see Moussiopoulous et al., , 1993 |
| Gaussian | GFLSM; Luhar and Patil, 1989 |
| Lagrangian | GEM-AG; see O'Neill et al., 2003 |
| Screening | UK DMRB; Highways Agency, 2009) |

A comprehensive overview of the different approaches adopted by dispersion models was documented by Holmes and Morawska (2006) and Namdeo et al. (2002).

It was discovered that in a UK research and governmental content Gaussian Dispersion Models are widely used due to their stability and the extensive validation performed on their outputs in recent years (Riddle et al., 2004). Thereby, these types of models are discussed in the following section.

### 2.8.1 **Gaussian Dispersion Models**

A number of Gaussian dispersion based area quality packages are available and Gaussian dispersion theory is used for the majority of air quality modelling in the UK (Gurjar et al., 2010). Gaussian models work based on the assumption that for a given wind direction pollutant concentrations are normally distributed in the vertical and horizontal planes. Additionally, Gaussian plume formula assumes that wind speed and turbulence are vertically homogenous and that crosswind dispersion is assumed to be uniform over a given meteorological wind sector (Vallero, 2008; Gurjar et al., 2010).

Gaussian models have been used in air quality modelling since the 1970s, for example the CALINE series (Benson, 1979). These models used a simplistic dispersion methodology. For example, these models did not take into account the effect of atmospheric chemistry or surface roughness on the dispersion of pollutants. Current air Gaussian air quality models use complex algorithms to calculate dispersion (CERC, 2006). ADMS-Urban (CERC, 2006) can adopt algorithms for dry deposition, wet deposition, particle settling and chemical reaction schemes (for calculating boundary layer parameters). The model also has an integral street canyon model for simulating air quality for a particular street segment surrounded by buildings (Namdeo et al., 2002).

Typically Gaussian air quality models distinguish between three types of emissions source: Line Sources; Point Sources; and Area/ Volume Sources (CERC, 2006). Road or vehicular emissions sources may be treated differently depending on the model selected. For example, in AERMOD road sources are modelled as a string of volume sources along a line segment (EPA, 2004). Whilst in ADMS-Urban and the Airviro Gauss mod, road sources are treated as a series of point sources (CERC, 2006).

### 2.8.2 **Limitations of Gaussian Air Quality Models**

Whilst modern Gaussian dispersion models ensure higher predictive power than that achieved with simplistic models, a multitude of input parameters are required. AERMOD requires upper air data, site-specific meteorological measurements, boundary layer height, surface albedo, surface roughness, cloud cover, Bowen ratio and a geographically and temporally resolved emissions inventory to be input prior to dispersion modelling (EPA, 2004). This complexity can be regarded as a limitation, as a simpler screening model is less data intensive.

Another limitation of Gaussian dispersion models is their performance when predicting concentrations in calm conditions (Vallero, 2008). Wind direction has an impact on model performance as predictive power is higher when air-flow is directed towards the receptor (Vallero, 2008).

Arguably the most significant limitation of Gaussian dispersion models is their performance in street canyons (Chatterton et al., 2008). As a result many modern air quality models include internal street canyon models. However, these internal models are generally relatively basic. ADMS-Urban, for example, comprises a simplified version of OSPM. This model has been shown to poorly predict pollution concentrations in street canyons (Westmorelands et al., 2007).

## 2.9 Transport Modelling

Both Stevenson et al., (1998); and Mitchell and Dorling (2003) conclude that since the mid-nineties transport is the main contributor to poor air quality in the UK's cities.

Therefore, accurate transport data is vital if air quality concentrations are to be correctly predicted using an atmospheric dispersion modelling. The calculation of road traffic emissions has been discussed in Section 2.7. However, whilst it is possible that the traffic data used in emissions modelling may be obtained from 'real-world' measurement, e.g. flow data obtained from automatic traffic counts (ATC) or manual classified traffic counts (MCC); and speed data, obtained from speed surveys, it is often the case that traffic data is collected from a transport model.

This may be because 'real-world' data is incomplete or unavailable, or it is difficult to arrange the available data in the format required for emissions modelling. Additionally, the use of a transport model for traffic data provision may allow the assessment of the impact on air quality of future traffic conditions, or alternative scenarios, for which real data will inherently be unobtainable.

A transport model is a representation of a transport system, built to simulate existing or future traffic conditions in order to inform a decision making process (SIAS, 2012). Transport models are useful in a variety of circumstances, from the illustration of current transport problems, to the forecast of potential problems that will occur in the future. They can also be used for environmental impact assessment and to justify significant infrastructure investment by demonstrating that a proposed scheme will provide financial or time saving benefits (SIAS, 2012).

Transport models are data intensive. They require information on the transport network; road/ junction characteristics, observations on the ground, details of driver behaviour, as well as traffic demand data, travel patterns, demographic data, public transport data, traffic signals information, growth forecasts, and development assumptions (DfT, 2001).

Transport modelling covers a significant scope of work which looks to cover public transport, walking and cycling as well as air, sea and freight. For the purpose of air quality modelling it is road transport which is responsible for the overwhelming majority of transport emissions (Stevenson et al., 1998; Mitchell and Dorling, 2003; Anderson, 2009; Balmes et al, 2010; COMEAP, 2010; DEFRA, 2011).

Scale is also an important consideration when contemplating transport modelling (DfT, 2001). The scale and purpose of a project or research task will determine the type of transport model most suitable. Whilst there is no coherent classification system for transport models, WebTAG (2014) recognises three different scales of transport modelling; micro-scale, meso-scale, and macro scale.

### 2.9.1 **Micro-scale**

Microsimulation models model the movements of individual vehicles (Shaw, 2015). Examples of microsimulation models widely used in the UK include VISSIM (PTV, 2016), S-Paramics (SIAS, 2012) and AIMSUN (TSS, 2016).

Typical uses of micro-scale modelling include; junction design, network improvements, monitoring traffic behaviour, and visualising impacts. The principle advantage of microsimulation modelling over traditional mathematical transport models is their ability to realistically represent driver behaviour (PTV, 2016). Driver aggressiveness, head way, risk attitudes and lane change behaviour can all be specified within the model to provide an accurate range of driver behaviours across the modelled network. Microsimulation is regarded as the closest to real-world that can currently be achieved in transport modelling (Shaw, 2015).

Microsimulation can be used to model individual junctions or a larger network. In reality programmes such as S-Paramics blur the lines between micro and meso-scale modelling and it is possible to model large areas including complete city road networks (SIAS, 2012). However, due to the extremely data intensive nature of micro-scale modelling it is often not practical to build and validate larger networks. Other limitations include the inability to model 'irregular' driver behaviour, and the time and cost associated with even small projects (TSS, 2016).

Due to the scale of area covered it is also possible to include Junction Modelling in the 'micro-scale' category. Examples of junction models include LINSIG (Moore, 2011), ARCADY, PICARDY and TRANSYT (TRL, 2012). However, whilst these models are more suited to modelling small areas, they are more traditional mathematical based models which do not consider individual vehicles, instead modelling traffic in an empirical manner (Highways Agency, 1996).

Microsimulation models can be used directly to provide input parameters for emissions modelling. Examples of their use in this process can be found in Section 0.

### 2.9.2 **Meso-scale**

As discussed the distinction between micro and meso-scale transport modelling is difficult to define (SIAS, 2012). Similarly, there is the potential for overlap with macro-scale modelling depending on the application of the model. Examples of where meso-scale modelling could be used include; determining changes in traffic routing, congestion mapping implementation, and municipal/ regional traffic control schemes.

The benefits of meso-scale transport models include the ability to model congestion over a wide area, wider impact assessment, and optimisation of multiple signals over a larger area than would be practical to model using a true micro-scale model (Grote et al., 2016). However, their use is less suited to detailed design of junctions or multi-modal modelling (SIAS, 2012).

Examples of meso-scale models are Aimsun (TSS, 2016), Dynameq (INRO, 2013) and Split Cycle Offset Optimisation Technique (SCOOT) (Moore, 2011). As with Aimsun, S-Paramics could also be regarded as a meso-scale model dependant on the scale and objectives of its application (SIAS, 2012).

As with microsimulation models, meso-scale models can provide outputs for emissions models. Either directly, using an IEM, or alternatively they could be interrogated to provide manual outputs in a format suitable for emissions modelling input parameters.

### 2.9.3 **Macro-scale**

Macro-scale transport models, also known as ‘strategic models,’ are used for the analysis of large scale major schemes, often at a regional or national level. Macro-scale modelling has the ability to illustrated wider changes in flow/delay and consider the consequences of strategic level planning. The outputs from macro-scale models are often exported into GIS to allow spatial analysis of the output parameters. They are able to process large amounts of demographic data, understand changes in demand, and provide exports for economic or environmental assessment (SIAS, 2012).

The majority of macro-scale transport models are made up of a number of sub models. For example, transport forecasting, accessibility, modal splits, public transport utilisation and the assignment of vehicles to the highway network (TSS, 2016). It is typically possible to use all, or only one of the sub models depending on modelling purpose. For example, for emissions modelling it would be expected that only a highway model would be used.

Examples of macro-scale transport models include SATURN (Simulation and Assignment of Traffic to Urban Road Networks) (Atkins Limited, 2014), VISUM (PTV, 2016), and CUBE Voyager /TRIPS (Citilabs, 2012).

Macro-scales models generally adopt a traditional travel demand forecasting model i.e. trip-based, using a hypothetical trip production-attraction (PA) matrix as the unit of travel analysis (Citilabs,2012). Such models are also often referred to as “four-step” models because they consist of four general process steps; trip Generation; trip Distribution; mode split; and traffic Assignment (Martens and Hurvitz, 2009).

The highways elements of macro-scale modelling usually include transport activity data and road vehicle fleet composition data. Typically activity variables include traffic flows, link and network speeds, road link delay, queue length and number of lanes on each link (Van Vliet, 1982).

Macro-scales models provide a simplified model of the highway network. They are not developed to include every link within the modelled area. Only links considered to have strategic significance are included, and links with low traffic volumes are unlikely to be included in the modelling network (Highways Agency, 1996).

Whilst macro-scale models can be used to provide traffic data for emissions modelling, there are limitations due to the nature of strategic level data. Whilst a macro-scale model may be validated across the wider modelled area, there is significant scope for significant error when considering small areas or model cordons (SIAS, 2012). Similarly, detailed design of junctions or detailed modelling of local roads is not advisable with strategic modelling (Highways Agency, 1996).

## 2.10 Geo-demographic Data

The IMD Geo-demographic Data used in this research were developed by the Social Disadvantage Research Centre at the University of Oxford, using 38 indicators which have been divided into 7 weighted domains including measures of income; employment; mortality; education; housing; crime; and living environment (Office of National Statistics, 2016). This index is available to download for each Lower Super Output Area (LSOA) from the Office of National Statistics. Data available includes the IMD score, rank of Index of IMD, and the individual score and rank of each domain with the IMD.

Similarly, Hospital Episode Statistics (HES) database was used in this research for the study in Chapter 4. HES data was obtained from the North East Public Health Observatory (NEPHO). Suitable International Classification of Diseases (ICD) codes were selected so that respiratory and circulatory illness could be accurately represented in accordance with the Committee on the Medical Effects of Air Pollutants (COMEAP) (COMEAP, 2010). All data was output at LSOA level. Further segmentation of the data, for example by age, was avoided to reduce data suppression (Gilmore, 2011). Reasoning and restrictions of the data are discussed in Section 4.2.8.

To complement micro-scale air quality modelling, household geodemographic data was obtained from Experian's Public Sector Mosaic database (Section 2.10). Household level Mosaic data was geocoded using OS Address-Point.

Geodemographic classifications provide a tried and tested means of measuring and monitoring small area conditions. They provide an accurate understanding of each citizen's demographics, lifestyles and behaviours by accessing a wealth of information on all UK individuals using more than 440 data elements (Experian, 2009). 62% of the data used comes from Experian's Consumer dynamics database, which sources information from a variety of databases including the electoral roll, credit and car ownership reports, the shareholders register, house sale prices and council tax bands. The remaining 38% of the data is sourced from Experian's current year estimates of the 2001 census (Experian, 2009).

Mosaic is based on analysis of the latest trends in UK society, a wealth of high quality, comprehensive data sources and a sophisticated proprietary approach to cluster analysis, supported by analysis of market research to validate the classification. Public Sector Mosaic customer profiling classifies all UK citizens into 15 groups (A to O) and 69 types (A01 to O69) (Appendix C). The data typifies the Mosaic group or type and does not infer information of the individual household explicitly. Thereby, Mosaic analysis provides a sharper definition of deprivation than can be obtained by using the Indices of Deprivation alone (Bhatt, 2013).

Mosaic also contains health data within its demographic data element and is commonly used by health professionals (Gilmore, 2011). Specifically, Mosaic contains data from the HES database (course health bands; cancers and others; and long term conditions); General Health Census data; a number of general health categories from the British Household Panel Survey (BHPS); and Sport England survey data. However, whilst the inclusion of heath data within the Mosaic is acknowledged, it is important that its use is appropriately understood in the context of customer profiling. Given that the database does not infer information of the individual household explicitly, assumptions on individual household parameters, such as health, should be avoided (Gilmore, 2011).

## 2.11 Personal Air pollution Exposure Estimation Studies

Personal air quality exposure monitoring studies aim to provide estimates for an individuals' exposure to a given pollutant (Tonne et al, 2018). Depending on the research aim, personal exposure studies could be generally categorised as measuring exposure to indoor and outdoor pollutants, although a number of studies explore exposure models covering both indoor and outdoor pollutants measurements (Freeman and Saenz de Tejada, 2002; Pérez Ballesta et al., 2008).

Numerous types of personal air quality exposure monitoring options have been conducted from static monitoring campaigns which physically monitor individual participants (Matar, 2015); diary and questionnaire surveys (Gerharz et al., 2009); to personal exposure estimate modelling (Kousa et al, 2002; Smith et al., 2016).

A wide body of studies and evidence suggests that personal exposure to air pollutants is not adequately understood because individuals spend time in different locations, within the home, at work/school, and in different travel microenvironments (Watson et al, 1988; Rotko et al, 2001; Rivas et al., 2017; Tonne et al, 2018).

However, whilst it is acknowledged that activities vary dramatically with age, gender, occupation, and socio-economic status, when considering environmental inequalities very few examples are based on personal exposure, those that are have tended to consider inequalities at the neighbourhood or area-level, rather than using individual-level socio-economic or ethnicity data (Hajat et al., 2015).

Tonne et al, (2018) attempts to consider air pollution exposure inequalities both at residence and using modelled personal exposure by utilising the London Hybrid Exposure Model (LHEM). This model is based on individuals who responded to the London Travel Demand Survey (LTDS), conducted by Transport for London to capture data on travel patterns and modal share. Socio-economic data too was obtained from the LTDS. This research found differences in inequalities in air pollution when estimated at residence versus personal exposure; and that exposure differed by age, income, and area-level income deprivation (Tonne et al, 2018).

The scope for these types of studies providing a more accurate assessment of the EJ of air quality is discussed in Sections 2.13 and 3.3, along with a statement of their limitations in the context of the research questions of this work.

### 2.12 Summary

The literature review presented in this chapter has shown that there is existing evidence of environmental injustice in the distribution and production of poor air quality. Concentrations of most pollutants are higher in urban areas, where there is also more concentrated deprivation. Furthermore, not only are deprived communities likely to be disproportionately exposed to the risks of air pollution, they are also disproportionately vulnerable to its effects.

However, whilst several studies suggest that low socio-economic status creates worse outcomes for exposure to air pollution, the association is not uniform. There are many sources and types of air pollution and policies around transport routes and green space can have important impacts.

Generally, the relationship between deprivation and air quality is poorly understood. In order to provide a detailed understanding of this relationship it is necessary to have a complete picture of air quality concentrations across an area. In an ideal world pollution concentrations would be continuously measured and monitored everywhere throughout a conurbation. However, this is neither physically nor financially feasible. Instead policy makers must rely on air quality models to predict the spatial distribution of pollutants over a given area.

Additionally, it is acknowledged that in the UK, since the mid-nineties transport is the main contributor to poor air quality in our cities, and the main cause of respiratory illness and deaths amongst vulnerable groups such as young children. Kelly and Fussell (2015) provide a comprehensive review of current sources of global air quality, including coal combustion, shipping, power generation, the metal industry, biomass combustion and dessert dust episodes. They conclude that road transport is the main source of urban air pollution throughout the worlds cities; and is also associated with the most serious health outcomes. Similarly, Karagulian et al. (2015), considering PM, conclude that traffic is the single most important contributor globally, although the importance of local specific industry sources is also highlighted. Moreover, 'domestic fuel burning' is identified as the largest pollution source contributor in Africa; and 'industry' has approximately twice the contribution than traffic in Turkey. Therefore, global, regional and local information and context is required.

Traffic data can be combined with emissions factors in a model to estimate the emissions from road traffic. There are a number of different techniques to develop emissions factors, namely, dynamometer tests, and real-world measurements. In the UK dynamometer tests are typically used to develop emissions factors. These factors are based on average-speed and vehicle type. It is widely acknowledged that there are major discrepancies between emissions factors and real world emissions. These differences have been attributed to, amongst others, the inability of the factors to take into consideration congested conditions. IEMs are able to address some of the limitations of average speed based models.

Once calculated, emissions outputs can be entered in to a dispersion model in order to provide estimates of pollutant concentrations. Commonly Gaussian dispersion models are used for the assessment and review of air quality in the UK. Whilst Gaussian models comprise a number of assumptions and limitations, comprehensive model evaluation using statistical and graphical descriptors can provide confidence in their outputs.

The interrogation of air quality outputs in conjunction with geo-demographic data can provide a detailed and diverse understanding of the EJ of the distribution of air quality across a study air. By varying the types of models used, and carefully selecting appropriate data sets it is possible to explore these themes across geographical scales.

### 2.13 Research Gap

Strong evidence of environmental injustice in the current distribution and production of poor air quality exists within the literature. However, the overwhelming majority of existing studies concentrate on the analysis of current or historic associations. As a result their methodologies do not allow for the analysis of future air quality strategies or schemes designed to improve air quality. A gap exists in understanding the EJ implications of air quality strategies or schemes designed to improve air quality.

Recent years have seen heightened political focus on policy and attempts to improve air quality. Whilst it is broadly suggested that improving air quality will also improve existing EJ concerns, evidence to date shows that even in situations where air quality is improving the rate of concentration improvement is lowest for the poor (Mitchell et al, 2015).

This research presents a suite of linked models of traffic, emission, dispersion, and geodemographic models (the modelling framework) that together allow not only the accurate assessment of existing EJ situation to be established, but also the assessment of future strategies and schemes designed to improve air quality, which may improve or exacerbate the existing EJ relationship.

Understanding the EJ implications of proposed air quality strategies or schemes has strong potential for aiding policy and decision making in this field. Whilst it is recognised that it is far beyond the scope of this PhD to identify measures which might be effective in reducing vehicle traffic, identified in the literature as the primary source of air pollution in the present day, understanding the future implications of identified policy areas could help guide policy development towards solutions that minimise inequality.

Moreover, the literature review has identified issues of geographical scale in understanding the relationship between the research themes. Mitchell and Dorling (2003) and later Mitchell et al (2015) completed a comprehensive review of environmental inequality studies, and subsequent further review of literature revealed a reliance on larger geographical scale datasets, such as IMD or Carstairs Index for geographical based EJ studies (Section 2.5.3). The limitations of larger scale datasets are discussed in Section 3.3 and stem from the granularity of the data when measured against the typical physical extents of areas with poorest air quality.

Thereby, a second gap exists in addressing the issue of geographical scale in area based EJ studies. The literature review identified that the use of microsimulation modelling in conjunction with an IEM model is now a well-established emissions modelling technique (Boultier et al., 2007). Whilst the use of IEMs generally is confined to the exploration of emissions outputs and not the subsequent dispersion of emissions in order to determine air quality (See Anttila et al, 2010; SIAS, 2012; and Hernández-Moreno and Mugica-Álvarez, 2014), there is identified scope for combining these techniques and applying them in the context of an EJ study in order to produce a modelling framework capable of household level EJ analysis of air quality strategies or schemes designed to improve air quality.

Moreover, a review of recent DMRB modelling guidance (Highways Agency, 2015) identified that the traditional approach to the vehicle emissions modelling using Defra's Emission Factor Toolkit was acknowledged to not accurately assess the impacts and benefits associated with introducing or removing periods of congestion within the air quality assessment. This is identified as being due to the reliance only on average 'speed' and flow to calculate emissions. Whilst the document goes on to suggest a

Speed Pivoting Methodology which addresses some of their concerns, it concludes that even the revised DMRB air quality spreadsheet model (v1.03c) cannot be used to calculate emissions and concentrations in congested conditions. Given IEMs offer a solution to this issue through combining speed, acceleration and flow in their emissions estimates (See Section 2.7.1) this provided further evidence that adopting their use within an air quality assessment should be explored in this research.

It is recognised that even household level geographical EJ assessment has its limitations. In reality an individual's personal exposure to air pollution is governed by a multitude of factors beyond their home address (See Section 2.11). It is possible to foresee that a 'big data' approach to large population personal air quality exposure may be possible in the future, however, limitations of current monitoring equipment and data collection methods ensure that such an approach is currently not feasible. Such an approach would address these limitations and arguably provide a more accurate assessment of EJ.

A large population, personal exposure based approach to air quality management may also have far wider implications for how air quality is managed throughout UK and the world, since AQMAs (or comparable areas such as Air Quality Management Districts such as in the U.S.A. are all geographically based, and linked to area receptors such as houses, schools or places of work (Durham County Council, 2016) (Section 2.3). It is difficult to imagine how air quality could be managed based on actual individual population exposure; however, one would speculate that whilst the concept of receptors would remain, the relative importance of air quality at the home address versus in public spaces and places of work may shift.

However, due to the aforementioned limitations of current technology, existing personal exposure studies are typically limited in sample size and duration, ensuring that current data sets are unlikely to represent a practical answer to assist strategy assessment or policy decision making. Furthermore, whilst such a holistic dataset would undoubtedly provide a powerful tool, and alter the direction of this research, active monitoring is still limited to gaining understanding of the existing situation, ensuring an element of scenario modelling would still be required.

CHAPTER 3

# 3. Methodology

## 3.1 Introduction

The literature review has identified established links between air quality, health and EJ. It has also identified numerous methodological issues associated with investigating these themes. As discussed in Section 1.2.2, this research has two aims:

1. To establish a modelling framework to explore the research themes and test the EJ of the distribution of air quality across scales within the study area (develop the base-case).
2. To apply the modelling framework to transport strategies and assess the extent to which these actions improve or exacerbate existing EJ concerns (scenario testing).

The aim and scope of this research has necessitated substantial modelling work. An accurate assessment of the level of air quality is a vital requirement for assessing the EJ of the spatial distribution of air quality across scales. Accurate air quality data is vital to be able to develop new policies and strategies. The ability to identify the impact of transport schemes or policy is paramount if such policies are to be successful.

This research seeks to enable the assessment of transport schemes or policy on air quality, as well as identify if those impacts improve or exacerbate the EJ of the spatial distribution of air quality. The literature review has identified that the vast majority of existing EJ research has been completed using methodologies suitable for identifying links in the existing data, but entirely incapable of predicting the impact of schemes or strategy on those links.

Therefore, an innovative framework has been developed in order to allow an assessment of the EJ impact of air quality management measures that may create only subtle changes in the traffic flow regimes.

### 3.2 Methodology framework

The modelling structure adopted in this research can be broadly separated into four main processes; the basic architecture of the modelling approach is outlined in Figure 3.

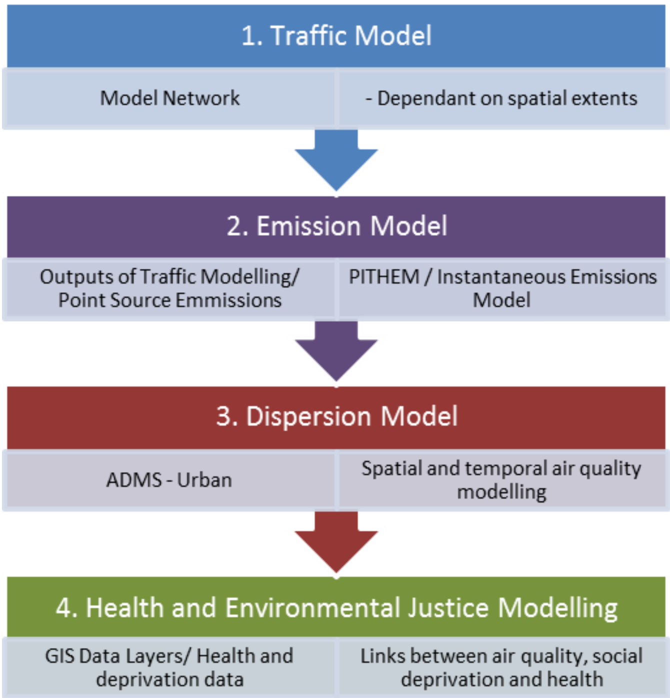



Figure 3. Modelling Outline Methodology.

Figure 3 describes the methodology applied in investigating the research themes and the processes adopted in order to produce results. The modelling framework is applicable across scales by varying the modelling processes at key stages. For example, emissions modelling is performed at two levels dependent on spatial scale. The use of microsimulation in conjunction with an IEM for case study work allows the greater data availability to be exploited. The use of PITHEM in conjunction with larger scale strategic models is suitable for wider mesoscale application.

Figure 4 outlines the methodology framework, details the datasets used at each model step across the following three results chapters, and identifies the methods and processes described in the following sections. The colour coding highlights which chapters and studies within, address the two aims of this thesis.

**Aim 1**

To establish a modelling framework to explore the research themes and test the environmental justice of the distribution of air quality across scales within the study area (develop the base-case).

**Aim 2**

To apply the modelling framework to transport strategies and assess the extent to which these actions improve or exacerbate existing EJ concerns (scenario testing).

***Scenarios:***

1. (Durham Traffic Engineering Scheme)

2. (VKT Reduction Scenarios 1-5)

| PhD Studies | **Chapter 4**<br>Pilot study to develop understanding of the research themes and modelling techniques. | **Chapter 5**<br>Comprehensive EJ assessment of air quality base case. Testing of application of framework across scales. | **Chapter 6**<br>Application of the modelling approach on transport strategies. Impact of transport strategies on existing EJ concerns. |
|---|---|---|---|
| Traffic Modelling | **Macro scale TPM model**<br>*Description:*<br>Section 3.4.1 | **Micro scale S-Paramics**<br>*Description:*<br>Section 3.4.2<br>(Durham study)<br><br>Macro scale TPM model<br>*Description:*<br>Section 3.4.1 (Newcastle & Gateshead studies) | **Micro scale S-Paramics**<br>*Description:*<br>Section 3.4.2 |
| Emissions Modelling | **PITHEM**<br>*Description:*<br>Section 2.6<br>*Use:* Section 4.2.2 | **AIRE IEM**<br>*Description:*<br>Section 2.7.1<br>*Use:* Section 5.2.1 | **AIRE IEM**<br>*Description:*<br>Section 2.7.1<br>*Use:* Section 6.2/6.3 |
| Dispersion Modelling | **ADMS Urban**<br>*Description:* (Sections 4.2.3 to 4.2.7) | | |
| Health and EJ Modelling | Health Data:<br>**Hospital episode statistics (HES) data** /<br>EJ Data:<br>**Indices of Multiple Deprivation (IMD)**<br>*Description:*<br>Section 2.10/ 4.2.8<br>*Use:* Section 4.3 | Health Data & EJ data:<br>**Mosaic Public Sector**<br>(Household Data)<br>*Description:*<br>Section 2.10<br>*Use:* Section 5.2.1 | Health Data & EJ data:<br>**Mosaic Public Sector**<br>(Household Data)<br>*Description:*<br>Section 2.10<br>*Use:* Section 6.4<br><br>***Scenarios:***<br>***1.*** (Durham Traffic Engineering Scheme)<br>(Section 6.4.1)<br>2. (VKT Reduction Scenarios 1-5)<br>(Section 6.4.2) |

Figure 4. Methodology framework

## 3.3 Methodology of this thesis

This section explains which of the transport, emissions, dispersion, and health and EJ review methods discussed in the literature (Sections 2.6 to 2.11) were selected to address the aims of this research and why.

During the literature and methodology review, it became clear that several modelling processes would need to be used to address the study's aims. The use of a pilot study (Chapter 4) allowed an understanding of the research themes and modelling techniques to be developed within the study areas as outlined in the introduction of Chapter 1. The pilot study helped shape both the methodical approach and datasets utilised in the subsequent studies (Chapters 5 and 6); as well as identifying that a more novel approach to EJ modelling was required than those identified in the literature in order to adequately address the research aims.

The Durham pilot study presented in Chapter 4 utilises a traditional macro-scale travel demand forecasting transport model, in conjunction with average speed based emission factors and an atmospheric dispersion model, to predict air quality concentrations across the study area. These outputs where then analysed using linear regression to test for association with deprivation (IMD) and health (HES) data. This approach was deemed appropriate following a review of the methodologies of similar studies by King and Stedman 2000; Pye et al 2001 and 2010; Linares et al 2004; and Namdeo and Stringer 2008.

Following the pilot study and further subsequent review of the literature a methodological review was performed and a number of modifications and additions where identified in order to address weaknesses in the traditional approach given the research aims. These weaknesses are discussed in Section 4.3.3.

In summary:

- the scale of air quality issues in Durham ensured a microscale assessment was required, suitable for assessing the research themes at the household scale; and
- there was evidence that the relationships between the themes were non-linear.

The implications of these findings for the subsequent EJ studies in Chapter 5 and 6 were as follows:

- A micro-scale transport model was used in place of the macroscale TPM model. A micro-scale model was considered more appropriate for the study extents given the spatial extents of Durham's air quality issues identified in the pilot study. These extents were identified as primarily the city centre, and represented a complex road network of interlinked junctions for which microsimulation is the more appropriate tool (PTV, 2016).

- Use of a micro-scale model would enable the use of an IEM to generate emissions outputs, enabling significant improvement in the prediction of air pollution (Boultier et al., 2007). The full advantages of using an IEM are discussed in Section 2.7.1. This variation in model approach was important for establishing the base case understanding of the EJ of the spatial distribution of air quality (Chapter 5). Furthermore, the use of an IEM was critical given the research aim of allowing the assessment of the EJ impact of air quality management measures that may create only subtle changes in the traffic flow regimes (Chapter 6). Particularly given the congested nature of the study area this benefit was of vital importance given the findings from the literature review, which acknowledged that the traditional approach to vehicle emissions modelling, using Defra's Emission Factor Toolkit or other speed derived emissions factors, does not accurately assess the impacts and benefits associated with introducing or removing periods of congestion within the air quality assessment (Highways Agency, 2015) (See Section 2.13).

- The large scale social demographic data (IMD) and health data (HES) used in the pilot were identified as unsuitable for use in a microscale study. Alternative data sets were sought that would allow for household level analysis of the research themes. A review of available household level data revealed a large focus on larger scale datasets in EJ and air quality research. Mitchell and Dorling (2015) completed a comprehensive review of environmental inequality studies, and subsequent further review of literature revealed a reliance on larger scale datasets, such as IMD or Carstairs Index (Section 2.5.3) for geographical based studies. Alternative approaches which regularly utilise household level data include personal air pollution exposure research (Section 2.11). However, this type of research generally involves original, single person data collection (e.g. Matar, 2015) and analysis of small data sets (e.g. Gerharz et al. 2009). Therefore, the use of geodemographic classification data was explored following discussion with health professionals (Gilmore, 2011). The use of Public Sector Mosaic data was investigated and selected for subsequent studies in Chapters 5 and 6, following licensing discussion with DCC and a review of suitability (Bhatt, 2013) (Section 2.10). The use of this data in conjunction with the revised modelling approach enabled an innovative approach to addressing the aims of this research.

- Finally, following the evidence that the relationships between the themes may be non-linear, an alternative statistical approach to exploring the relationships was investigated for the subsequent studies. As discussed in Section 4.3.3 it is acknowledge that there is scope for additional nonlinear statistical analysis in the pilot study. However, given the aforementioned weaknesses of the pilot with regards scale and dataset, it was deemed more appropriate to utilise resource to address those limitations through the development of more thorough subsequent studies with an enhanced dataset better suited to nonlinear statistical analysis. For example, the available social demographic data in the pilot study is at LSOA level (1500 mean number of residents; 52 LSOA's in the study area); whereas the use of geodemographic classification data in the microscale EJ analysis in Chapters 5 and 6, utilises household level data across 7471 households in the study area, allowing for more robust statistical analysis of non-linear trends. Details of the revised statistical approach to assessing the data in Chapters 5 and 6 can be found in Section 5.2.

Exploring the connection between air quality and EJ has been explored by research in the past (Section 2.5). However, only a minority of these studies utilise methodologies capable of exploring change in air quality distributions.

For example, Mitchel et al, 2015; Pye et al 2010; and Davoudi and Brooks, 2012, use the UK's air quality mapping provided by Ricardo-AEA Ltd under contract to the government (DEFRA) to meet EC statutory reporting. Average outputs from this dataset are subsequent compared against LSOA level social demographic. These air quality maps use the national atmospheric emissions inventory to produce an aggregate map of existing atmospheric concentration, calibrated and verified against a network of air quality monitoring stations data (Mitchel et al, 2015).

Utilising the UKs reported air quality mapping, or other existing air quality datasets, including the use of directly monitored air quality data (For example, see Miranda et al, 2011) is a justifiable and valid methodology for exploring existing connections between air quality and environmental justice.

However, the ability to consider change in existing air quality distribution is fundamental to answering the research questions posed in this research. Namely, the impact of air quality strategies on existing EJ concerns. Therefore, this research successfully combines a novel approach to air quality scenario modelling, with more traditional EJ statistical analysis techniques used to explore existing EJ relationships.

One key example of a comparable study to this research is presented by Namdeo and Stringer, 2008. This work used a series of linked models of traffic, emission and pollutant dispersion to explore the relationship between air pollution, social deprivation and health in the city of Leeds. Furthermore, given that the air quality inputs in this research where based on linked modelling, the research was further able to examine this relationship under three further scenarios. Three distance-based road user charging (RUC) scenarios set at 2 pence, 10 pence and 20 pence/km were explored, and the result concluded that RUC scenarios result in reducing disparity between affluent and deprived populations (Namdeo and Stringer, 2008).

This research can, to an extent, be regarded as an effort to build on the methods and findings of the previous work by Namdeo and Stringer (2008). However, the modelling techniques used by Namdeo and Stringer (2008) vary significantly to those adopted for the final results chapters of this research; and the considered transport strategies differ substantially (i.e. RUC scenarios versus VKT reductions to meet EU air quality and carbon reduction targets; and a transport engineering scheme in Durham's AQMA). Moreover, the latter of these differences necessitated the former. Namely, the requirement to consider air quality scenarios resulting from only subtle changes in traffic flow regimes.

The modelling approach in Namdeo and Stringer (2008) involved the application of a chain of dynamic simulation models of traffic flow (SATURN, SATTAX), pollutant emission (ROADFAC) and dispersion (ADMS-Urban), integrated within a geographic information system model PITHEM (Namdeo et al., 2002).

PITHEM was initially utilised in the pilot study in Chapter 4 of this research (Sections 2.6 and 4.2.2). However, as discussed earlier in this section, the specific requirements of this research led to the use of microsimulation modelling and an IEM to generate emissions prior to dispersion, in contrast to Namdeo and Stringer's strategic level SATURN and PITHEM based approached. Nonetheless, despite the significant change in approach, the concept of using a chain of dynamic simulation models to investigate EJ scenarios remains a common theme.

Similarly, the use of microsimulation modelling in conjunction with an IEM model is now a well-established modelling technique (Boultier et al., 2007). However, the author is not aware of this modelling approach being adopted for use in an EJ study. Moreover, the use of IEMs is generally confined to exploration of emissions outputs and not the subsequent dispersion of emissions in order to determine air quality (See Anttila et al, 2010; SIAS, 2012; and Hernández-Moreno and Mugica-Álvarez, 2014).

It was therefore necessary to use bespoke programming to enable the IEM derived emissions outputs to be suitably formatted for use in the ADMS dispersion model. Given the vast amounts of data created when using an IEM, Microsoft Visual Basic for Applications (VBA) was used to develop a programme capable of processing the emissions data outputs in a manageable and timely manner. This enabled the use of an IEM, in place of more traditional NAEI derived emissions factors, to be incorporated in to the modelling framework as described in Section 5.2.1. Furthermore, this modelling technique required the development of a 24 hour microsimulation model in order to develop 24 hour emissions profiles as described in Section 3.4.2.

Whilst the process of model selection described above and detailed in the following sections evolved in order to allow the research questions to be better addressed, the overarching limitation described in the research gap review remains valid (Section 2.13). As discussed, even the developed household level geographical EJ assessment has its limitations given that an individual's personal exposure to air pollution is governed by a multitude of factors beyond their home address (See Section 2.11).

However, as discussed, due to the limitations of current monitoring equipment and data collection, existing personal exposure studies are typically limited in sample size and duration, ensuring that current data sets are unlikely to represent a practical answer to assisting in wider strategy assessment or policy decision making. As such a population exposure based approach to EJ assessment remains an impractical approach for this research. Furthermore, whilst such a holistic dataset would undoubtedly provide a powerful tool, and alter the direction of this research, monitoring is still limited to gaining understanding of the existing situation, ensuring an element of scenario modelling would be required. For these reasons, a geographical, or area based EJ assessment was identified as the most appropriate for this research.

The following sections of this chapter provide details of the transport modelling performed in the thesis. The selection and preparation of transport model was critical given the objective of assessing the extent to which transport schemes and policy address existing EJ concerns, careful consideration and preparation, calibration and validation was required to ensure suitability.

The emissions, dispersion and EJ modelling processes were less onerous in terms of building and preparation. As such it was more appropriate to provide the details of their use within the discussion of the research. Relevant sections to find relevant discussion can be found in Figure 4 of this section.

## 3.4 Transport Modelling

The issue of scaling in this research is discussed in Section 2.9 and in the conclusions in Chapter 7. Two separate modeling scales are explored in this study, namely, macro scale and micro scale.

### 3.4.1 Macro scale TPM model

The macro-scale transport model utilised for this research was a multi-modal model, referred to as the Transport Planning Model (TPM). This model was developed by Newcastle City Council (NCC) on behalf of the Tyne & Wear (also including Gateshead Council, North Tyneside Council, South Tyneside Council, Sunderland County Council and Nexus (The Passenger Transport Executive)) Joint Transport Working Group (JTWG). The model was built following the completion of a Strategic Transport Model (STM) which was applied to support the Local Transport Plan (LTP2) developed by the Tyne and Wear JTWG.

The TPM is a modern four-stage transport model which models trip generation, mode split, distribution and assignment. The model was built based on the principles and guidance included in the DfT's WebTAG. Both highway and public transport networks were developed for three periods (morning peak, inter-peak and evening peak periods). The productions and attractions (Base matrices) were generated from national and local land-use data. Base Year trip patterns are partly informed by trip data from traveller intercept surveys which provide details of movements and journey purposes, also by the local household interview survey and supported to an appropriate degree by matrix estimation processes to allow modelled flows to reflect traffic count data (NCC, 2012).

The TPM was specified and built using two different software platforms: OmniTRANS mainly for Base matrix development and validation and CUBE/TRIPS for all other components to take advantage of the particular merits of both software suites. Both software packages have been integrated into the TPM modelling system.

The TPM geographically represents a significant part of North East England and in particular the Tyne & Wear (T&W) metropolitan area and wider region. The area covered by the model includes the five T&W Districts (Gateshead, Newcastle, North Tyneside, South Tyneside and Sunderland), the remainder of the Study Area and then in decreasing detail neighbouring areas and the rest of Great Britain. The Study Area relates to the Census Travel to Work area, the 'catchment area' of trips into T&W for work purposes.

For this research two separate cordons of the model were utilised. Firstly, for the City of Durham EJ study; and secondly for the EJ studies of Newcastle and Gateshead. Specific details of these study areas can be found in Section 4.1 and Section 5.3 respectively. Both these cordons fell within the most detailed core area of the model (the TPM model comprises 504 zones, of which zones 1 to 88 are within the core Tyne and Wear County area, See Figure 5).

The model is regarded as up-to-date with modern practice and among the most soundly-based transport models of its type in the country providing a comprehensive and up-to-date representation of the Tyne & Wear transport networks (NCC, 2012).

Limitations of TPM (and macro modelling in general):

- The highway assignments do not include the effects of queues blocking back to interfere with other junctions or of flow metering where congestion reduces downstream flows. This is particularly limiting for emissions modelling.
- The goods vehicle matrices reflect common practice but are certainly a weak reflection of reality.
- Coarse matrices, household and RSI survey data
- Due to the large scale of the model the accuracy of specific areas of interest cannot be assured despite validation against counts and / or journey speeds according to DMRB criteria.

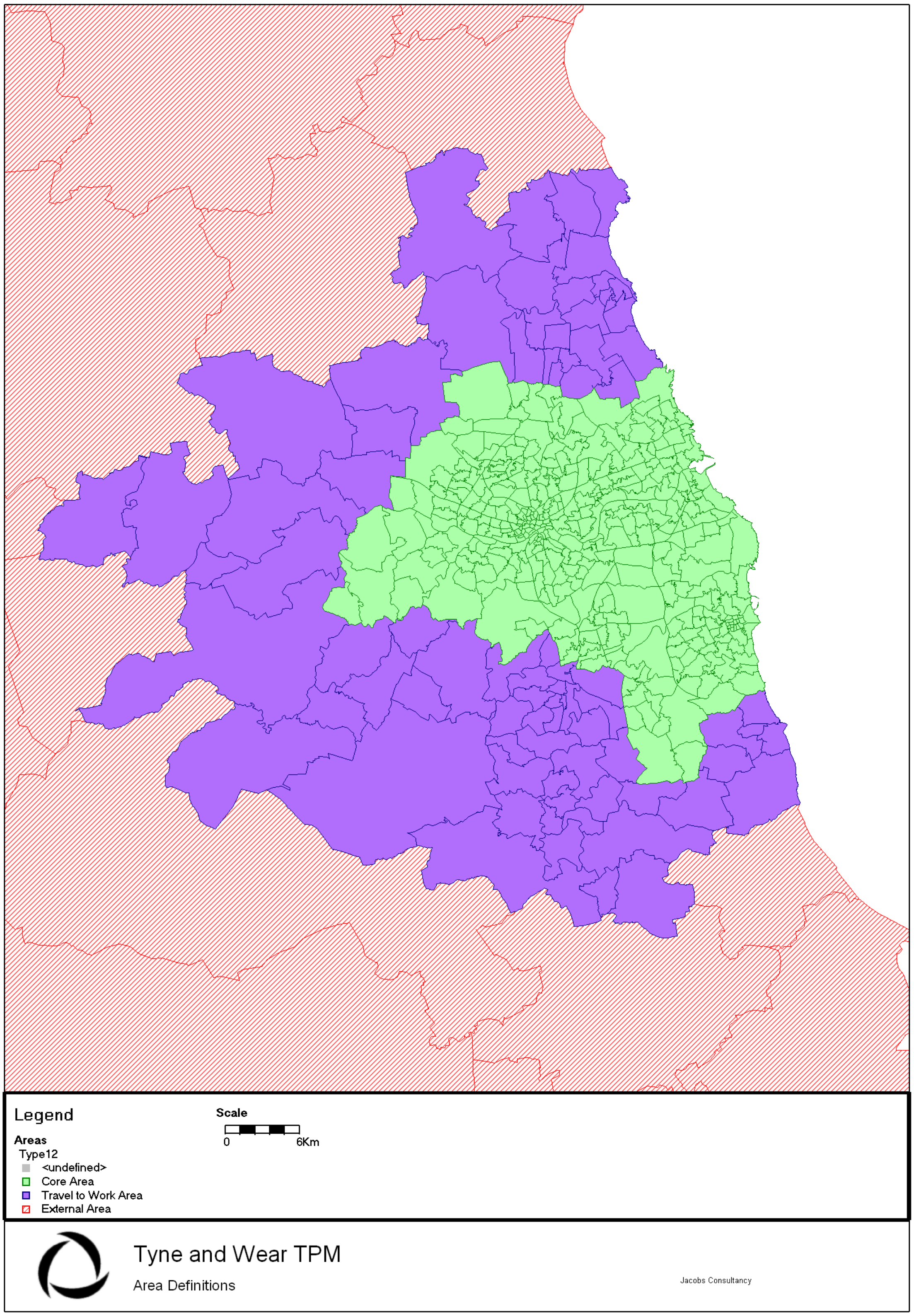



Figure 5. TPM Study Area and Zoning System Newcastle City Council (NCC, 2012)

### 3.4.2 Micro-scale model

Durham County Council's (DCC) S-Paramics©) microsimulation model has been utilised for all micro-scale assessment work conducted for this research.

The reasons for using microsimulation traffic modelling in this research are discussed in Section 2.9.1 and 2.7.1 which explore the benefits of microsimulation; and microsimulation in conjunction with an IEM respectively. In summary, microsimulation is regarded as the closest to real-world that can be achieved in transport modelling (Highways Agency, 1996); and, as microsimulation models can be used directly to provide input parameters for IEMs, the benefits of IEMs can be realised. These benefits over traditional average speed based approaches include their ability to capture the variability in emissions associated with both speed and acceleration; and detailed spatial resolution outputs enabling significant improvement in the prediction of air pollution (Boultier et at., 2007) (Section 2.7.1).

The decision to use S-Paramics, as opposed to other examples of microsimulation models widely used in the UK, for example, VISSIM (PTV, 2016) and AIMSUN (TSS, 2016) (Section 2.9.1), was made for two primary reasons. Firstly, the availability of licensing and access to the model provided by Durham County Council made the research feasible. Whilst the Durham Paramics model required significant updating, recalibration and revalidation (See Sections 3.3, 3.4.2 and 3.5) it nonetheless provided a start point from which to develop an appropriate modelling tool. Secondly, the availability of licensing for AIRE IEM ensured its suitability. Whilst AIRE can be used in conjunction with the outputs from any traffic microsimulation model, it was specifically developed for use with S-Paramics (SIAS, 2012).

The Durham model was developed by SIAS and Durham County Council covering the core area of Durham City in detail and significant sections of surrounding highway network including major routes incorporating the A1, A167, and A691.

The model extents broadly include Chester-le-Street to the north; Stanley, Brandon and Crook to the west; Newton Aycliffe and Spennymoor to the south; and Peterlee, Seaham and Houghton-le-Spring to the east. The study area is defined in Figure 6.

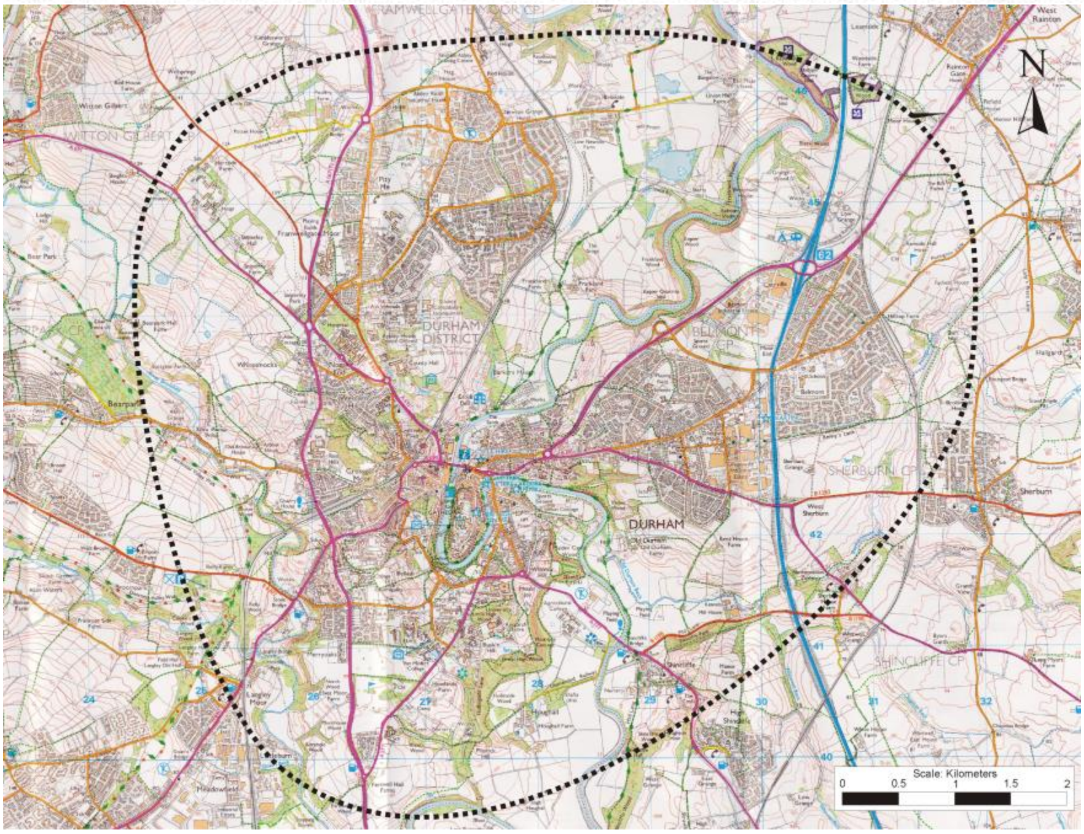



Figure 6. Base Network Construction (Adapted from Durham County Council, 2007).

The model is a full 4-stage transportation model which models trip generation, distribution and mode split based on the distribution of trip productions and attractions. These productions and attractions are generated from national and local land-use data; trip patterns are generated using trip data from intercept surveys which provide details of movement patterns and journey purposes. Where such data is not available, traditional matrix estimation processes are employed to match modelled flows to traffic count data.

The primary model network was built based on digitised Ordnance Survey mapping, with an extensive survey completed to determine additional network operation information such as location of stop lines, lane markings and actual lane usage.

All links within the study area were coded as either a major or a minor highway link. Minor links were coded where roads were classed as either local distributor roads, or residential access roads.

DCC provided signal timing data for all junctions and pedestrian crossings within the modelled area. Pedestrian crossing timing frequencies were selected to reflect high and low pedestrian demand as advised by DCC.

Public transport information was supplied including:

- Location of bus stops within the study area;
- Dwell times at key Bus Stops (in the absence of dwell time data 'high usage' and 'low usage' times were selected of 20 and 10 seconds respectively. These values were agreed based on DCC engineering judgement and information from previous data collection exercises (Durham County Council, 2015);
- Bus route information, including service and route number; and
- Bus service frequency data.

The model periods developed were AM Peak (06:30 - 09:30), and PM Peak (15:00 - 18:30) as well as a build-up Interpeak model. Each peak hour has been modelled with a 'warm up' period to reflect the build-up of demand prior to the simulation model's peak period. This warm up period is not calibrated or reported, it populates the simulation with vehicles so the peak demand is based on an already active network rather than an empty network. By the end of the warm up period, the simulated traffic demand has built up to a sufficiently realistic level to accurately represent the flow conflicts present during the core peak period.

There are no requirements for the minimum length or volume of the warm up period, rather it is user defined and specific to the scheme. The fundamental requirement is to ensure the warm up period achieves a realistic traffic demand for the beginning of the core peak period. The warm up period for Durham model is determined by the length of time it takes a vehicle to travel between the furthest extents of the model. A volume of 80% of the peak demand was used.

An additional 'warm down' period has also been included for the Durham models to ensure all vehicles entering the network during the peak period leave via their destination during the simulation period, negating the potential for inaccurate results towards the end of the peak periods.

Trip Matrix Assignment

The core area comprises 149 zones, based on Census output areas, and split as appropriate to provide a suitably disaggregate level of zoning including areas such as housing, industry and schools. The core area zones are shown in Figure 7.



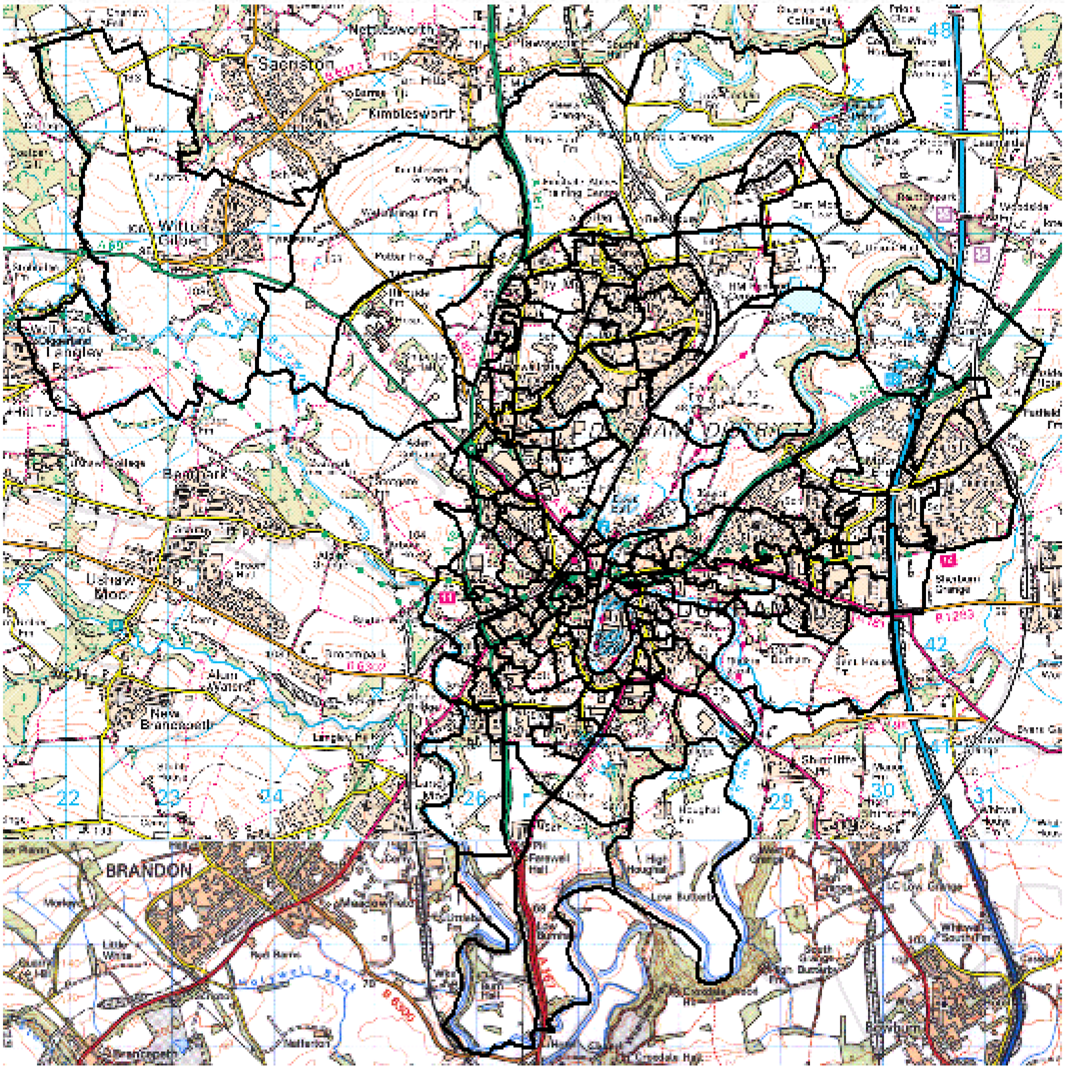



Figure 7. Core Area Zones Durham Paramics (Adapted from Durham County Council, 2007).

A further 14 zones were defined to represent route zones on the 14 principal roads entering the modelled network as shown in Table 3. These are larger zones, generally representing surrounding towns and villages such as Sunderland, Chester-le-Street and Washington to the north; Stanley, Brandon and Crook to the west; Newton Aycliffe, Spennymoor and Sedgefield to the south; and Peterlee, Seaham and Houghton-le-Spring to the east. The network coding for the travel to work area is derived from the Tyne & Wear Transport Planning Model.

Table 3 Definition of Route Zones

| Route Zone | Road |
|---|---|
| 901 | A167 (South) |
| 902 | A690 (South/West) |
| 903 | Stonebridge |
| 904 | Toll House Road |
| 905 | A691 |
| 906 | B6532 |
| 907 | A1 (South) |
| 908 | A167 (North) |
| 909 | Red House |
| 910 | A1 North |
| 911 | Pittingdon Lane |
| 912 | Front Street (Sherburn) |
| 913 | A177 Shincliffe |
| 914 | A690 (East) |

The origin-destination trip matrices used in the Durham model were constructed from an earlier CONTRAM (CONtinuous TRaffic Assignment Model) model. The existing CONTRAM model contained the A167, A181, A177 and A690 corridors along with a comprehensive cover of all distributor roads and minor residential access roads. CONTRAM is a Windows-based program jointly developed by Mott MacDonald and TRL for modelling traffic flows, queues and delays. CONTRAM models drivers' route choice through urban or inter-urban networks and the consequent queues and delays they experience (Durham County Council, 2007).

Sector analysis was used within Paramics to evaluate the CONTRAM Matrix. Zones are grouped in East/ West for example and the volume crossing the bridge can be assessed. Further groups of zones are sectored enabling a series of checks to be undertaken to highlight the volume of trips at key locations. The calibration and validation of vehicles flows across the network can be found in Section 3.5 and 3.7.

Vehicle Classifications

Within microsimulation modelling the vehicle type assigned has an influence on acceleration, braking and the size of the vehicle (PTV, 2016). All these factors contribute to the behaviour of the vehicle within the simulation.

Classified junction turning counts were used to derive global vehicle classifications for the Durham network. The vehicle classifications and percentages can be seen in Table 4.

Table 4 Vehicle classifications and Percentages

| Vehicle Class | AM Period | PM Period (and off-peak) |
|---|---|---|
| Cars | 82% | 84% |
| Light Goods Vehicles | 12% | 12% |
| Heavy Goods Vehicles | 6% | 4% |
| Passenger service vehicles (buses) | Fixed route | Fixed route |

The decision to use global vehicle classifications was made following earlier attempts to use vehicle class matrices in the Durham model. Whilst individual matrices would allow greater control over the fleet characteristics on individual routes their use in the modelling proved too cumbersome for the scale of the model. Due to the large spatial extent of the model each additional classified matrix set slowed the running time by approximately half and the model became unreliable and prone to crashing. It was therefore decided to revert to using global vehicle classification figures.

Due to the limited availability of off-peak classified data it was decided to use the PM period global figure as this most closely followed the few counts that were available.

Demand Profile

A series of demand profiles were applied to different origin- destination movements within the model. Demand profiles create the appropriate peak surges in key areas of the model resulting in suitable peak time queues.

Profiles were created from analysis of traffic data obtained from DCC. Where possible, 15 minute count data was used to enable a more accurate representation of peak surges. For movements where count data was not available, a general demand profile was used to complement the available data. This profile was based on traffic information from suitable primary routes as determined by DCC. All 14 principal road entry zones were assigned individual demand profiles. Significant effort was sought in determining the accuracy of these profiles, as movement between these zones was responsible for 88% and 89% of AM and PM peak traffic respectively. Flow profiles were not classified by vehicle type due to the limited availability of classified count data.

Examples of the AM and PM peak general profile can be found in Figure 8 and Figure 9.

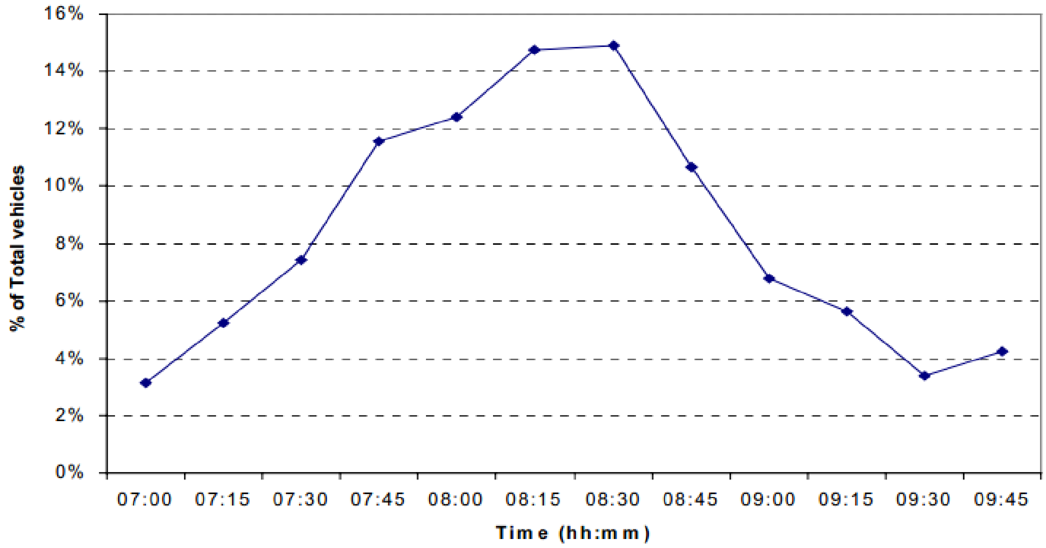



Figure 8. AM Peak Durham Profile

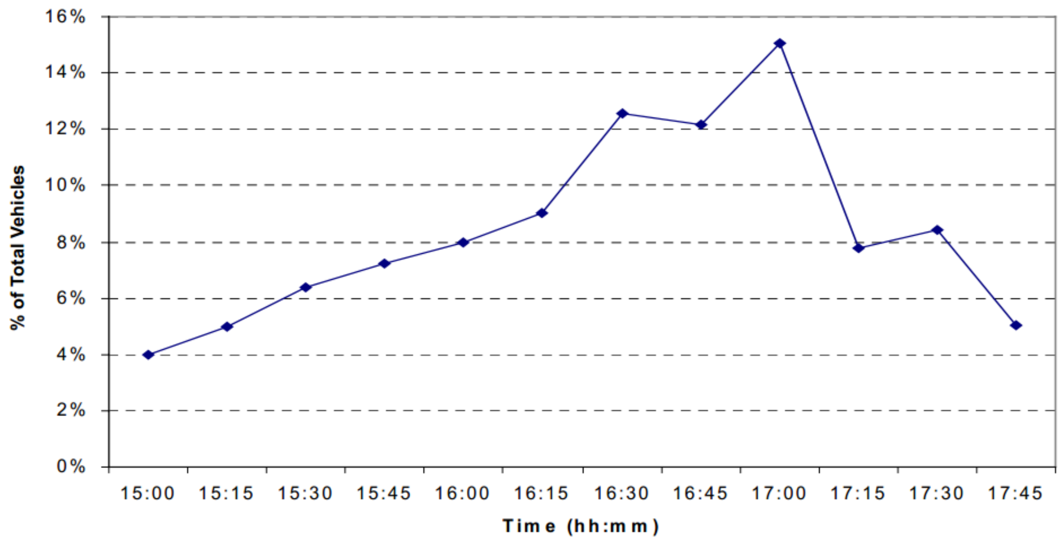



Figure 9. PM Peak Durham Profile

Additionally, when adapting the model for use with gaining 24 hour emissions outputs it was necessary to create a series of 24 hour emissions profiles. A similar methodology was applied for creating these profiles although due to the limited availability of off peak traffic data only four Durham central zone profiles were created, as well as individual profiles for the 14 principal road entry zones. The decision as to which of four Durham central zones profiles to apply to specific origin – destination movements was determined based on DCCs experience of flow regimes throughout the city area.

Furthermore, the 24 hour profiles were only applied outside of the peak periods and only aggregated to an hour frequency. This was due to the limited availability of off peak 15 minute traffic counts.

The four 24 hour Durham central zone profiles can be seen in Figure 10.

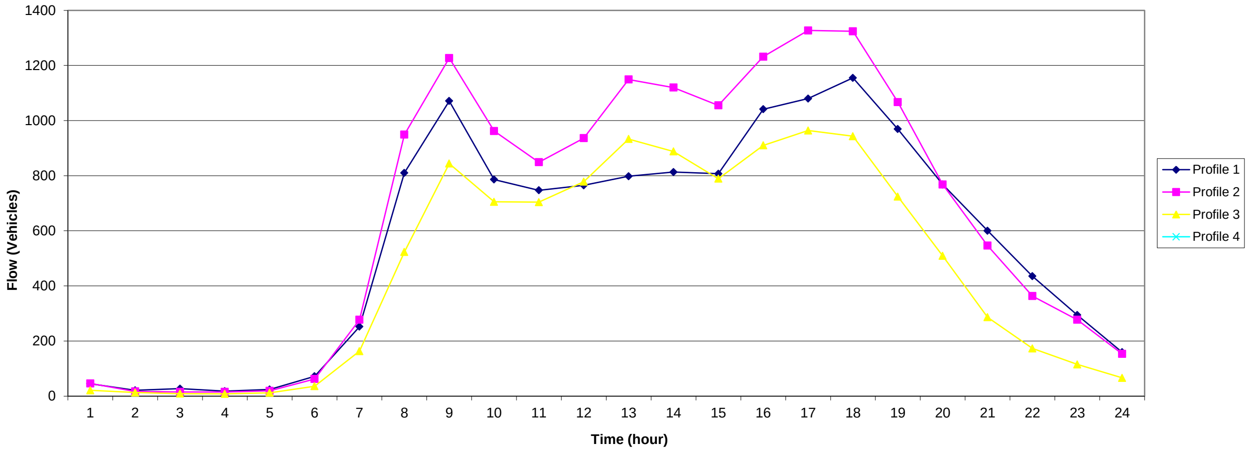



Figure 10. 24 hour Durham Central Zone profile

*Route Choice Methodology*

Within the Durham Paramics model each microsimulation vehicle has a choice of routes to its destination. SIAS (2012) assert the number of routes and the probability of a vehicle using a route is determined by the following factors:

- Category as major/minor route
- Familiarity
- Time and distance coefficients
- Perturbation; and
- Dynamic feedback.

The impact of major/ minor routes is influenced by familiarity. ‘Familiar’ drivers see the links costs as they are calculated, whereas ‘unfamiliar’ drivers see the cost of all minor links factored by two. This results in unfamiliar drivers preferring major routes to minor routes, whilst familiar drivers have no preference. In the Durham model the proportion of familiar drivers was set to 60% (Cars and LGVs) and 85% (HGV and buses). These figures were chosen after consultation with DCC and SIAS.

The basic assignment model within Paramics is an All or Nothing routine whereby all vehicles will select the minimum cost path based upon the generalised cost criterion specified by the programme (SIAS, 2012). Additionally, supplementary functions are available within Paramics to enable a more realistic set of route choice decisions to be made. Dynamic re-routing has been used in Durham to allow drivers to react to congestion and delay on the network. Information on route delays is fed back in to the simulation to enable a reassessment of the optimum route to any given destination. This dynamic feedback allows a degree of variation between selected routes and ensures that not every vehicle will make the same route choice between a given origin-destination pair. This route choice methodology could be described as multiple user class stochastic assignment (PTV, 2016).

Traditional methods of model convergence as detailed in DMRB 12.1.2 are therefore inappropriate for assessing a Paramics model, since they were derived for, and only relevant to, equilibrium models such as TRIPS and SATURN (Citilabs, 2012).

Further adaptions to ensure the model was suitable for use with an IEM included:

- Gradient - The addition of gradients in the model ensured that the existing calibration/ validation was no longer valid. The model was therefore re calibrated/ validated as per IMDB Guidelines – See Sections 3.3, and 3.5-3.7;

- Building of 24 hour matrix - A 24 hour matrix was built using traffic count data from 40 sites following IMDB Guidelines. Building and assigning the traffic matrix was required to capture emissions during off peak periods (Section 3.4.2).

- Traffic Signals - Signal timing specifications for all Durham City junctions were reviewed. On peak signal timings were amended as necessary as part of the model update process; and off peak signal timing plans were added to ensure the model was representative of read world conditions during the additional off peak periods (Section 6.2).

- Public transport data - Bus routing and timing data was updated to include off peak services.

- Proposed modelling (scenario testing) - Changes were made to reflect the VKT traffic reduction strategies; and proposed scheme detailed in Chapter 6. This included creating signal timings for two signalised roundabouts using LinSig v2 Both peak and off peak signal timings were generated (Section 6.2).

### 3.5 Durham Paramics Model Calibration

Calibration is defined as "a process of tuning and refining the input data and parameters within the model in order to agree with real observed data, and then provide a tool which is reliable for forecasting" (DfT, 2001). A key aspect of calibration is the comparison of simulated link flows outputted from the Paramics model to input link flows derived from the derived matrix. Model calibration is an iterative process requiring modifications to both the construction of the network, including calibration of parameters within the models, and to the input trip matrices. Figure 11 summarises this iterative process.

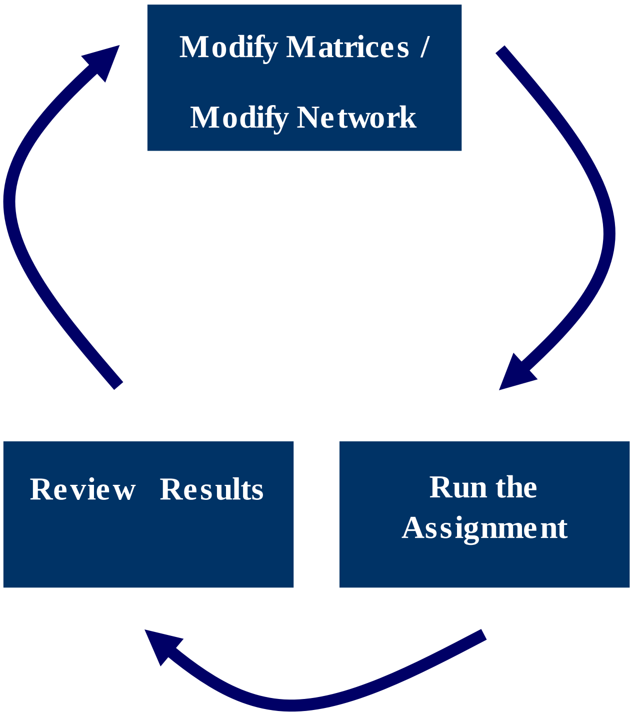



Figure 11. Paramics Model Iterative Calibration

The objective of model calibration is to ensure that the flow parameters entering the model are reflected in appropriate outputs, indicating the model is operating as desired.

Model validation (See Section 3.7) is the next step and seeks to demonstrate that the base model is suitable for use in scenario testing mode by comparing the modelled outputs to independent empirical data. During the Durham model update, calibration and validation have been considered in an integrated manner such that calibration and validation outputs have been generated for each model developed during this iterative process.

### 3.5.1 **Flow Calibration Requirements**

In this Durham Paramics model, flow calibration is based on determining the 'goodness of fit' of modelled link flows outputted from the Paramics model to the corresponding spreadsheet derived matrix link flows. Section 3.4.2 describes the trip matrix assignment process adopted for this modelling, highlighting the iterative process of assigning a trip matrix.

The criteria used to assess whether the correspondence is satisfactory are those described in Chapter 4 of the Design Manual for Roads and Bridges (DMRB) Volume 12, Section 2 and summarised below in Table 5**.**

Table 5 DMRB Cross-Sectional Calibration/Validation Acceptability Guidelines

| **Criteria Measures** | **Acceptability Guidelines** |
|---|---|
| *Modelled hourly flows compared with observed flows* | |
| Individual flows within 100 for flows <700 vehicles per hour (vph) | For 85% of cases |
| Individual flows within 15% for flows 700–2,700 vph | For 85% of cases |
| Individual flows within 400 vph for flows >2,700 vph | For 85% of cases |
| *GEH Statistic:* | |
| Individual flows: GEH < 5 | For 85% of cases |
| Total flows: GEH < 2 | For 85% of cases |
| Total flows: GEH < 4 | For all cases |

*Source: DMRB, Volume 12, Section 2*

It can be seen from Table 5 that the criteria recommended in DMRB for link flow calibration relates to firstly the margin of error of individual flows, and secondly to the GEH statistic, where GEH is defined as:

$$GEHStat = \sqrt{\frac{\{O - M\}^2}{\frac{1}{2}\{O + M\}}}$$

With: O = Observed traffic flow
M = Modelled traffic flow

The reason for including the GEH statistic is the inability of either the absolute difference or relative difference to cope over a wide range of flows. For example, an absolute difference of 100 vehicles per hour (vph) may be considered a big difference if the flows are of the order of 100vph, but would be unimportant for flows of the order of several thousand vph. Equally, a 10% error in 100vph would not be important, whereas a 10% error in say 3,000vph might mean the difference between constructing an extra lane or not.

Generally speaking, the GEH parameter is less sensitive to such problems since a modeller would probably feel that an error of 20 in 100 would be roughly as bad as an error of 90 in 2,000, and both would result in a GEH statistic of approximately 2. As a rule of thumb, when comparing modelled traffic flows with observed traffic flows, a GEH statistic of 5 or less would indicate an acceptable fit, whilst links with a GEH statistic of greater than 10 would require closer attention (Highways Agency, 1996).

### 3.5.2 **Visual Calibration**

Throughout the model construction and calibration process there were ongoing visual assessments and reviews of the modelled network operation to refine and reinforce the accurate representation of the empirical network operation. This comprised both internal and external reviews as described below.

### 3.5.3 **Internal Review**

The internal review was undertaken during the model development as an ongoing process. The qualitative information provided from onsite reconnaissance provided the basis for the majority of the initial review process. Particular attention was paid to identifying and addressing the following:

- All priority rules have been correctly coded so that vehicles give way in an appropriate manner;
- Lane utilisation at junctions is as observed during site visits;
- Where restricted lane usage by vehicle type exists, this is correctly represented;
- Observed driver behaviour and flow patterns are replicated at junctions and roundabouts;
- Modelled queues are representative of observed queues and take place at locations and at times expected based on observational evidence;
- Ensuring all banned and restricted turns are correctly modelled in all simulations;
- Yellow box rules have been input into the simulation where appropriate so that vehicles do not pass through each other in simulations, but in particular to ensure that junctions do not gridlock at key locations when highly congested. Such "gridlocking" cannot ever be entirely eliminated from a network for all possible patterns of traffic demand, since particular blocking problems only become apparent under particular patterns of trip matrix movements; and
- Addressing "errors" or "warnings" such as vehicles not able to enter the network due to congestion.

### 3.5.4 **External Review**

As part of the calibration process, some of the simulation runs were demonstrated to staff from the DCC Traffic team. This gave the opportunity for qualitative comments concerning the operation of the network and the realism of the simulated network in comparison to existing conditions regarding queuing patterns and congestion. This feedback proved invaluable with comments received forming part of the iterative calibration process.

### 3.5.5 **Calibration Results – AM Peak**

**3.5.5.1** Random Seed Variance Testing

In order to provide statistical confidence in the Durham microsimulation model it was necessary to undertake several runs, each with different random seeds. Ten different random seeds were run for the AM peak period, the results of which are detailed in **Appendix B** and summarised in Table 6 below.

Table 6 Random Seed Variance Testing: AM Peak (0800-0900) Results

| Seed | Sum of Absolute Difference to Average (aggregated results) | |
|---|---|---|
| | Vehicles | % |
| 1 | 124 | 1.9% |
| 2 | 77 | 1.2% |
| 3 | 103 | 1.6% |
| 4 | 71 | 1.1% |
| 5 | 103 | 1.6% |
| 6 | 88 | 1.4% |
| 7 | 100 | 1.5% |
| 8 | 84 | 1.3% |
| 9 | 117 | 1.8% |
| 10 | 62 | 1.0% |

It is evident from Table 6 that the Durham AM peak Paramics model produces consistent results with all 10 random seeds runs within 1.9% of the average for aggregated traffic flows.

**3.5.5.2** Traffic Flow Calibration

A key objective of the base model calibration process is to demonstrate that Paramics model achieves a similar throughput of traffic to the input flow data derived from the spreadsheet derived matrix.

Table 7 summarises the results obtained for 26 traffic flows collected at sites around the modelled network for the AM time period (0800–0900). Modelled flows outputted from the Paramics model have been compared to input flows from the spreadsheet derived matrix against the DMRB criteria summarised in Table 5.

It can be seen from Table 7 that the flow calibration results satisfy all DMRB count related criteria for all traffic flows during the morning peak period modelled hour.

Table 7 Count-Related Traffic Flow Calibration: AM Peak

| Statistic | Recommended Criteria | Paramics Model Results 0800-0900 |
|---|---|---|
| Number of counts compared | n/a | 26 |
| Maximum GEH for 85% of links | <5 | 2.5 |
| Average GEH for 85% of links | <2 | 1.1 |
| Average GEH for 100% of links | <4 | 1.5 |
| counts <700 vph (Maximum Absolute difference of 85% of links) | <100 vph | 28 |
| counts between 700 to 2,700 vph (Maximum Absolute difference of 85% of links) | <15% | 7.1% |
| counts >2,700 vph (Maximum Absolute difference of 85% of links) | <400 vph | N/a |

Individual traffic flow calibration for the morning peak hour is summarised in Table 7. It is evident from the summary results that the Paramics model output traffic flows are similar to the spreadsheet matrix model input traffic flows with 100% of the 26 traffic flows reviewed satisfying the criteria of GEH <5 for the AM peak period.

### 3.5.6 **Calibration Results – PM Peak**

#### **3.5.6.3 Random Seed Variance Testing**

Ten different random seeds have been run for the PM peak period, the results of which are detailed in **Appendix B** and summarised in Table 8.

Table 8 Random Seed Variance Testing - PM Peak (1700-1800) Results

| **Seed** | **Sum of Absolute Difference to Average (aggregated results)** | |
|---|---|---|
| | **Vehicles** | **%** |
| 1 | 88 | 1.3% |
| 2 | 185 | 2.7% |
| 3 | 140 | 2.0% |
| 4 | 100 | 1.4% |
| 5 | 99 | 1.4% |
| 6 | 73 | 1.0% |
| 7 | 113 | 1.6% |
| 8 | 144 | 2.1% |
| 9 | 104 | 1.5% |
| 10 | 115 | 1.6% |

It is evident from Table 8 that the Durham Paramics model produces consistent results with all 10 random seeds runs within 2.8% of the average for aggregated traffic flows.

#### **3.5.6.4** Traffic Flow Calibration – Traffic Flows

Table 9 below summarises the results obtained for 26 traffic movements collected at sites around the modelled network for the PM time period (1700–1800).

It can be seen that the calibration satisfies the count related criteria set out in DMRB for modelled traffic flows.

Table 9 Count-Related Traffic Flow Calibration - PM Peak

| Statistic | Recommended Criteria | Paramics Model Results |
|---|---|---|
| | | 1700-1800 |
| Number of counts compared | n/a | 26 |
| Maximum GEH for 85% of links | <5 | 2.5 |
| Average GEH for 85% of links | <2 | 1.6 |
| Average GEH for 100% of links | <4 | 1.9 |
| counts <700 vph (Maximum Absolute difference of 85% of links) | <100 vph | 52 |
| counts between 700 to 2,700 vph (Maximum Absolute difference of 85% of links) | <15% | 6% |
| counts >2,700 vph (Maximum Absolute difference of 85% of links) | <400 vph | N/a |

Individual traffic flow calibration for the evening peak hour is summarised in Table 9. It is evident from the enclosures in Table 9 that the majority of sites satisfy the GEH <5 criteria. The Paramics model output traffic flows are very similar to the spreadsheet matrix model input traffic flows with 100% of the 26 traffic flows reviewed satisfying the criteria of GEH <5 for the PM peak period.

### 3.5.7 Parameter calibration

Parameter calibration has also been considered in accordance with micro-simulation modelling guidelines set out by the Department for Transport (DfT) (2001). These guidelines describe the requirement to demonstrate that the parameters used in the microsimulation model (whichever software is used) are specifically tested and selected to produce the expected vehicle behaviour.

The key overall driver behaviour parameters are driver aggression and awareness distribution and network headway factor. In line with SIAS's recommendations the Durham Paramics model did not require alterations to the global parameters affecting driver behaviour. Driver behaviour fluctuates in response to specific road circumstances, and network wide changes are not recommended unless a sound case can be made that drivers behave differently across the modelled area in its entirety (SIAS, 2012).

Table 7 and Table 9 summarises the parameter calibration undertaken as part of the Durham model build. Included in Table 10 are details of the respective default parameters in Paramics, indicative ranges from the emerging HA guidelines, and an identification of the parameters adopted in the Durham Paramics model with an associated commentary.

Table 10 Parameter calibration

| Micro-Simulation Parameter *(Table 2 in HA Guidelines)* | Criteria | Unit of Measurement | Default value in Paramics | Guidance / Indicative Ranges from HA Micro-Simulation Guidance | Values used in Durham Paramics Model | Comment |
|---|---|---|---|---|---|---|
| **Mean Headway** *(Mean headway between vehicles at differing traffic speeds)* | Motorway links | Metres or Seconds | 0.9 seconds *(CC1 parameter)* | Cross reference defaults to mean headways (±10%) in Figure 5.1 in HA Guidelines. | 0.9 seconds | CC1 default parameter in Paramics is based on European driver behaviour so no justification to deviate from default. |
| | Freeway links | | | | | |
| | Off-line highway links | | | | | |
| | Urban links | | No default – speed dependant | | Speed dependant on local road network feeder link | |
| **Minimum Gap** *(Minimum acceptable gap between vehicles)* | Merge | Seconds | No default – speed dependant | Give way: 1.5 to 3.5 seconds<br><br>Roundabout 1.0 to 4.0 seconds | Speed dependant | Minimum gap parameters adjusted to reflect localised conflicts throughout the Durham Paramics model. |
| | Lane Change | | | | | |
| | Give Way | | 3 seconds (controlled by priority markers) | | Modified based on site specific junction performance | |
| | Roundabout | | | | | |
| **Vehicle Dynamics** *(Acceleration and deceleration profiles and the impact of gradient on vehicle performance)* | Car & LGV - Acceleration | $m/s^2$ | 3.5 | Cross reference defaults in HA Guidelines.<br><br>Figures 5.2 and 5.3 for light vehicles.<br><br>Figures 5.4 and 5.5 for HGV vehicles. | 3.5 | The default power and weight distributions of MGVs and HGVs within Paramics were adjusted in accordance with UK MGV and HGV manufacturer specifications. |
| | Car & LGV - Deceleration | | 2.8 | | 2.8 | |
| | Car & LGV - Power | kW | 50-120 | | 50-120 | |
| | Car & LGV - Weight | kg | 700–1,500 | | 700–1,500 | |
| | MGV - Acceleration | $m/s^2$ | 3.5 | | 3.5 | |
| | MGV - Deceleration | | 2.8 | | 2.8 | |
| | MGV - Power | kW | 50-120 | | 50-120 | |
| | MGV - Weight | kg | 700–1,500 | | 1,500-7,500 | |
| | HGV - Acceleration | $m/s^2$ | 2.2 | | 2.2 | |
| | HGV - Deceleration | | 1.3 | | 1.3 | |
| | HGV - Power | kW | 100–500 | | 100-500 | |
| | HGV - Weight | kg | 2,800-40,000 | | 7,500-42,000 | |

| **Micro-Simulation Parameter** *(Table 2 in HA Guidelines)* | **Criteria** | **Unit of Measurement** | **Default value in Paramics** | **Guidance / Indicative Ranges from HA Micro-Simulation Guidance** | **Values used in Durham Paramics Model** | **Comment** |
|---|---|---|---|---|---|---|
| **Desired Speed Distribution**<br><br>*(Desired speed from which the driver will sample on entry to the model)* | - | N/a (specify desired speed distribution curve) | Variable depending on link type | Seek to replicate speed distribution curve shown in Figure 5.6 of HA Guidelines for a 70 mph Motorway | Profiled in accordance with DfT transport statistics. Each link within the Paramics model has been assigned the appropriate speed distribution. | Speed distribution curves for cars and HGVs produced in accordance with DfT statistics (2005) reflect the shape of the curves in Figure 5.6 of HA Guidelines.<br>These speed distributions include a proportion of traffic which will not adhere to the 70mph speed limit (assuming free-flow conditions) therefore considered realistic. |
| **Driver awareness of vehicles around them**<br><br>*(Number of vehicles that it is assumed that a driver observes ahead in making his decisions on lane changing etc)* | - | Number of vehicles / distance | 2 vehicles and 250m look ahead distance for all link types | 2 vehicles appears sensible, but can be increased to 5 vehicles with minor effects. | Driver awareness adjusted to reflect link types:<br>Freeway : 5 vehs, 300m<br>Motorway : 5 vehs, 300m<br>Rural : 5 vehs, 250m | Look ahead distances increased to 300m and 5 vehicles for motorway links and merges/diverges (freeway links) to reflect the fact that motorway drivers will look further ahead and hence be more aware of other vehicles on the network. |
| **Influence of signing on the approach to a diverge on the motorway on lane selection**<br><br>*(Modelling how vehicles move across and when to make the move in order to* | - | Metres | 200m (although varies depending on network modelled) | Recommended approach is to enable the probability of lane changing [to diverge off the mainline] to be spaced out along a stretch of the motorway. | Typically set at 800-1200 metres from junction diverge to reflect motorway signing. | Paramics adopts the recommended approach of enabling lane change to be spaced out, reflecting mainline signing.<br>Model performance has been observed through calibration to ensure that inappropriate weaving is not taking place and that excessive queuing does not occur in the nearside lane due to significant |

| **Micro-Simulation Parameter** *(Table 2 in HA Guidelines)* | **Criteria** | **Unit of Measurement** | **Default value in Paramics** | **Guidance / Indicative Ranges from HA Micro-Simulation Guidance** | **Values used in Durham Paramics Model** | **Comment** |
|---|---|---|---|---|---|---|
| *leave the motorway)* | | | | | | volumes of traffic seeking to move across early. |
| **Co-operative Merging** *(Treatment of merging traffic and the co-operative nature of main line traffic)* | - | N/a (behavioural action) | No single parameter | Incumbent on the modeller to state how this behaviour has been modelled. | No specific values. | Co-operative merging (merge-in-turn) is done automatically as part of the behaviour model Priority rules (including replicating yellow box operation) have been used throughout the model, in particular at the boundary with the urban network in order to model co-operative merging. |
| **Implied capacity at roundabouts and signal stop lines** (Replicating observed entry capacities at roundabouts and stopline saturation flows at traffic signalised junctions) | - | N/a (dependent on junction form) | N/a Micro-simulation models do not have input values for capacity and saturation flow | Incumbent on the modeller to provide output data that shows the effective outturn capacity for key points and hence demonstrate that reasonable values have been used. | Empirical traffic signal timings have been used. Headway and gap acceptance have been defined to reflect site specific geometry. | |
| **Minimum distance between vehicles at standstill** | - | metres | 1.5m for all link types *(CC0 parameter)* | 1.5m between vehicles (range of 1.0m to 2.0m) | 1.5m for all link types | Through motorway slip road flow and queue calibration described above, Paramics default value of 1.5m between vehicles is considered to be appropriate. |

### 3.6 Calibration Summary

The stability of the base AM and PM peak Durham Paramics models were tested using 10 random seed runs during each peak period with the average of the ten used for reporting against the DMRB criteria. At an aggregate level, Paramics outputs for traffic flows satisfied all DMRB criteria.

Based on calibration results and iterative adjustments undertaken as part of the calibration process (including network and matrices modifications and adjustments to parameters), the base Durham Paramics model is considered to calibrate sufficiently to be taken forward for validation.

Due to the 24 hour nature of pollution modelling it was necessary to expand the Durham Paramics model to cover a full 24 hour day as detailed in Section 3.4.2. To enable the expansion of the modelled period, off-peak matrices were developed based on scaled traffic factors and the peak matrices. Full 24 hour calibration of the model was not deemed appropriate as the peak hour calibration provided confidence in the performance of the matrices when applied to the modelled network, and the off-peak matrices expansion was subject to separate checks (See Section 3.5). However, 24 hour validation of the model performance against independent empirical data was performed to provide confidence the model reflected real world conditions throughout the modelled day (See Section 3.7 and Appendix B).

### 3.7 Validation

Validation is defined as the qualitative comparison of data produced by the network model with data not used as a constraint in the model calibration or the direct estimation of the accuracy of the model data. The principle behind it is to check that the calibration is valid and to assess the quality of the information provided by the model (Highways Agency, 1996).

As described in Section 3.7, validation and calibration are integrated processes and as such have been considered at each stage of model development in order to understand model weaknesses.

It is important to recognise that the validation outputs from the Paramics model would not be expected to achieve the same level of agreement with independent data (in terms of DMRB criteria) as that achieved for calibration.

The validation of the base Durham models focuses on comparing simulated Durham link flows to independent ATC link flow data, obtained from permanent traffic counters by DCC. Error messages outputted from Paramics have also been reviewed to ensure that all vehicles exist within the network and are not erroneously removed. 24 hour traffic flow validation was carried out across the modelled network to ensure the models suitability for emissions modelling using an IEM (Section 3.4.2.).

### 3.7.1 Traffic Flow Validation

To present a robust validation process 28 link flows were examined against available validation traffic flow data provided by DCC.

Detailed hourly validation results are provided in **Appendix B**. Table 11, Table 12 and Table 13 provide a summary of the link flow validation results at 28 data collection sites for the AM Peak, PM Peak and complete 24 hour modelled period respectively.

Table 11 Link Flow Validation: AM Peak hour

| Statistic | Recommended Criteria | Paramics Model Results |
|---|---|---|
| | | 0800-0900 |
| Number of counts compared | n/a | 28 |
| Maximum GEH for 85% of links | <5 | 1 |
| Average GEH for 85% of links | <2 | 0.5 |
| Average GEH for 100% of links | <4 | 0.7 |
| counts <700 vph (Maximum Absolute difference of 85% of links) | <100 vph | 23 |
| counts between 700 to 2,700 vph (Maximum Absolute difference of 85% of links) | <15% | 2.6% |
| counts >2,700 vph (Maximum Absolute difference of 85% of links) | <400 vph | 56 |

Table 12 Link Flow Validation: PM Peak hour

| Statistic | Recommended Criteria | Paramics Model Results |
|---|---|---|
| | | 1700-1800 |
| Number of counts compared | n/a | 28 |
| Maximum GEH for 85% of links | <5 | 1 |
| Average GEH for 85% of links | <2 | 0.5 |
| Average GEH for 100% of links | <4 | 0.7 |
| counts <700 vph (Maximum Absolute difference of 85% of links) | <100 vph | 23 |
| counts between 700 to 2,700 vph (Maximum Absolute difference of 85% of links) | <15% | 2.6% |
| counts >2,700 vph (Maximum Absolute difference of 85% of links) | <400 vph | 56 |

Table 13 Link Flow Validation: 24 hour Period

| Statistic | Recommended Criteria | Paramics Model Results<br>24 hour period |
|---|---|---|
| Number of counts compared | n/a | 28 |
| Maximum GEH for 85% of links | <5 | 1 |
| Average GEH for 85% of links | <2 | 0.5 |
| Average GEH for 100% of links | <4 | 0.7 |
| counts <700 vph (Maximum Absolute difference of 85% of links) | <100 vph | 23 |
| counts between 700 to 2,700 vph (Maximum Absolute difference of 85% of links) | <15% | 2.6% |
| counts >2,700 vph (Maximum Absolute difference of 85% of links) | <400 vph | 56 |

### 3.8 Application of modelling tools to research

This section details how the modelling framework and modelling tools described in the wider chapter have been applied in order to explore the core research themes of this thesis.

To provide assurance on the devised modelling framework's suitability for investigating the research themes, the modelling framework has been applied in Durham at the meso-scale in Chapter 4. As well as testing the suitability of the core framework, applying it enabled an understanding of the EJ of the spatial distribution of air quality across Durham at the meso-scale. Furthermore, the pilot was used to identify limitations which were addressed in more detailed micro-scale assessments of EJ in subsequent chapters.

Reflecting on the current literature and building upon the outcomes of Chapter 4, the second phase of the research aims to provide a comprehensive EJ assessment of air quality in the North East through two distinct studies presented in Chapter 5. Firstly, to improve understanding of local level interactions, a fine spatial resolution case study was conducted centred on the City of Durham. Therefore, a nested modelling approach was adopted to allow the EJ investigation to be conducted across scales. The micro-scale study aimed to address some of the shortcomings of a meso-scale study by addressing issues of scale and air quality model performance. Secondly, to compare and contrast findings from the studies in the City of Durham, two further meso-scale studies of Newcastle upon Tyne and Gateshead provided insight into the EJ of these areas, as well as determining the suitability of the modelling framework in different areas within the north east of England.

Finally, building on findings from the micro-scale study described in Chapter 5, which reveals that the adopted modelling approach significantly improves the performance of dispersion modelling when measured against monitored data, it was acknowledged that the performance enhancement came due to the ability to more accurately estimate vehicle emissions in congested traffic conditions. Therefore, research is developed in Chapter 6 which aims to exploit this ability by completing a congestion sensitive assessment of traffic management solutions for air quality and low carbon goals that may create only subtle changes in traffic flow regimes. Therefore, the application of the modelling approach was tested through investigations into two distinct transport strategies. Firstly, the impact of a traffic engineering scheme aimed at reducing network emissions (specifically $NO_2$), as well as congestion and delay, was tested. Secondly, reduced VKT strategies were tested to assess the reduction in traffic required to meet various carbon and air quality targets under varying fleet assumptions.

Additionally, the impact of air quality and carbon management measures on existing EJ concerns were assessed using the methodology outlined in the ‘existing scenario’ micro-scale EJ assessment presented in Chapter 5. As in the previous micro-scale study Durham was selected as an appropriate study area (Chapter 4).

### 3.9 Accumulation of Errors

It is important to consider the accumulation of errors when conducting any research. The scope for issues surrounding accumulation of errors increases when conducting research across multiple themes and modelling processes using large and varied data sources (Garnett, 2016). In this research, deprivation data is analysed against modelled air quality, based on modelled emissions outputs, themselves based on outputs from a traffic model. Despite the presence of calibration and validation at each stage of the modelling framework, it could be considered that a risk of accumulation of errors exists. However, whilst a risk of accumulation of errors is present in this research, in reality the modelling framework presented is reliant on, and validated against, external empirical data at the key final step of the modelling process. Base case modelled air quality outputs are validated directly against observed concentration values collected from diffusion tubes. Statistical analysis, including use of fractional bias using the methodology of Chang and Hanna (2005), indicates no systematic under or over-prediction for the modelled results (Section 4.3.1 and 5.2.2.1). This provides resolute confidence that the air quality outputs are within an acceptable level of accuracy, despite any potential presence of accumulation of error in the preceding emissions and traffic modelling.

The importance of the air quality modelling validation step is noted, as whilst validation at each step of the modelling framework is independent from the process that went before, the risk of accumulation of errors is present in the preceding steps to the air quality modelling (i.e. traffic and emissions modelling). This risk is present as whilst during the development of the IEM used in this research the emissions outputs produced were validated against laboratory derived emissions outputs during the PHEM project (Section 2.7.1), it was not deemed feasible to conduct independent validation of the specific emissions outputs generated in this study (i.e. independent validation against data from instrumented vehicles or similar (Section 2.7.2)).

Overall, it is considered that the robust validation process adopted across the modelling framework developed in this research has successfully mitigated against the risk of accumulation of errors.

## 3.10 Summary

This chapter has provided an overview of the modelling framework developed in this research; and a comprehensive description of the modelling tools adopted, including the necessary calibration and validation techniques performed.

CHAPTER 4

# 4. Application of Modelling Framework in Durham

To provide assurance on the devised modelling frameworks suitability for investigating the research themes, the modelling framework has been applied in Durham at the meso-scale in this chapter.

## 4.1 Meso-scale Durham Pilot

As highlighted in Chapters 1 and 3 and in Chapter 2, the Literature Review, there is a strong requirement for research into the EJ of the spatial distribution of air quality. In addition, none of those studies have investigated this within the context of the North East region.

Therefore, this chapter provides details of a pilot undertaken in the City of Durham aimed at satisfying two key objectives. Firstly, to provide assurance on the modelling framework's suitability for investigating the research themes, the modelling framework described in Section 3.2 has been applied in Durham at the meso-scale. Secondly, an understanding of the EJ of the spatial distribution of air quality across Durham is sought at the meso-scale.

Information on the City of Durham and its suitability for a case study area has been discussed in Chapter 1. In the context of this pilot, 'City of Durham' refers to an area shown in Figure 12 covering approximately 72 square miles stretching from Pittington, Sherburn and Ludworth in the east, to Bearpark and Witton Gilbert in the west and encompassing all of Durham City centre. The district was actually abolished as part of the 2009 structural changes to local government in England; all functions of principal authority local government are now administered by the unitary council DCC (Durham County Council, 2007).

An overview of the methodology adopted for the pilot is given in Section 4.2 below. The results, discussions and conclusions are given in subsequent sections.

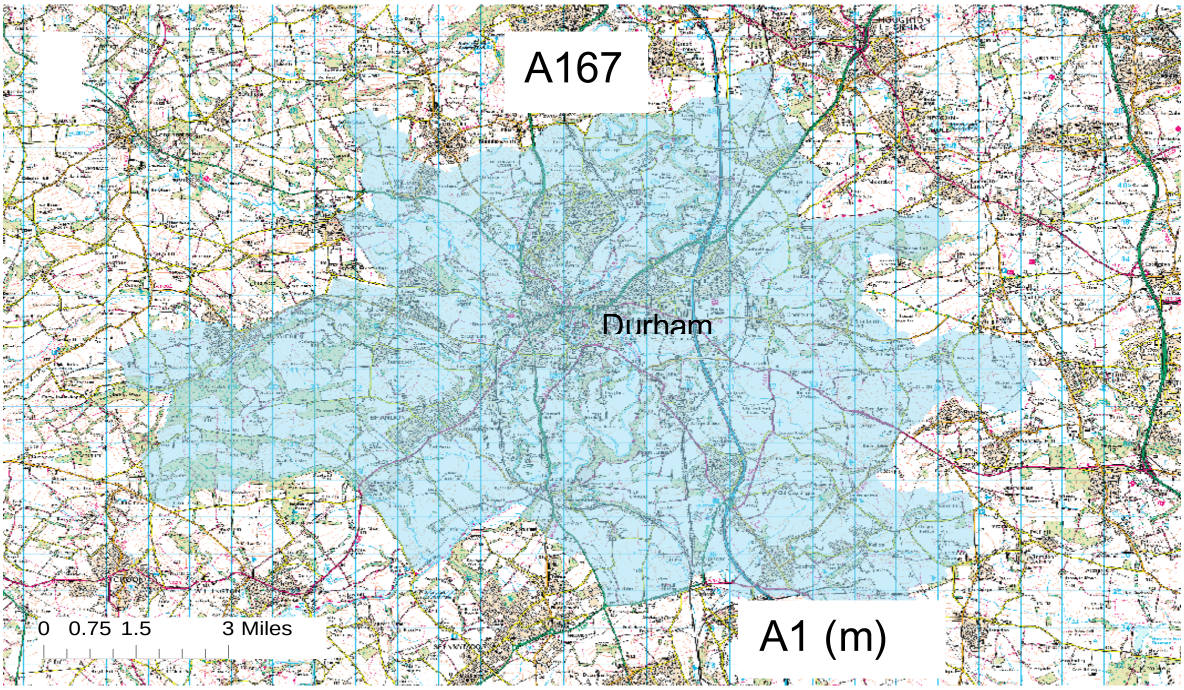



Figure 12. City of Durham Pilot Study Area.

## 4.2 Methodology

The modelling structure presented in Chapter 3, Figure 3 has been expanded below to provide details of the modelling and data packages adopted for the meso-scale Durham pilot study.

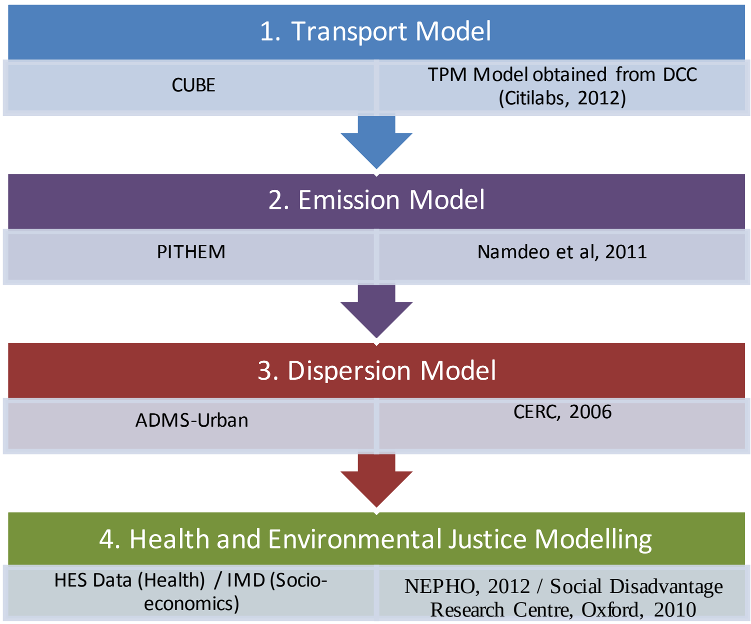



Figure 13. Meso-scale Durham Modelling Methodology

### 4.2.1 Transport Data

The traffic data used in this research was derived from the Transport Planning Model (TPM). The strategic TPM was built using CUBE Voyager (Citilabs, 2012). The base year for the modelling was 2010. Details of this highway model can be found in Section 3.4.1. The TPM was cordoned using a sub-model within the CUBE program to reflect the size and shape of the City of Durham district (Atkins, 2012). After the cordon process a total of 5491 links were present in the modeled network.

In order to ensure the traffic data from the TPM was suitable for emissions modelling, it was necessary to convert the modelled peak hour flows to provide 24 hour annual average hourly traffic flows. DCC (2011) provided expansion factors to enable the calculation of annual average daily flow (AADF) and diurnal profiles (Table 14). The expansion factors were derived from empirical traffic data and enabled the expansion of the peak hour and Inter peak (IP) values. Expansion factors are used to convert hour totals into flow figures that represent traffic in an average 24 hour period, or AADF. AADF represents the number of vehicles estimated to pass a given point on the road in a 24 hour period on an average day in the year (DfT, 2016). It is understood that in order to produce the provided expansion factors DCC followed a methodology similar to that described in the DfT's "Road Traffic Estimates – Methodology Note" (DfT, 2016). The AM, IP and PM expansion factors were applied to the corresponding peak flows obtained from CUBE.

Table 14 Expansion factors provided by DCC (2011) used to calculate annual average hourly traffic flows.

| **Period** | **Factor** |
|---|---|
| AM Peak Period: 07:00-10:00 | 2.4 |
| IP Period: Pre 07:00, 10:00-16:00, Post19:00 | 6.5 |
| PM Peak Period: 16:00-19:00 | 2.6 |

Total hourly traffic flows for each link were calculated. Completed profiles were then transformed to meet the input requirements of AMDS-urban on a link by link basis (profiles must average one and add up to 24; CERC 2006).

Expansion factors that enabled the development of Saturday and Sunday profiles were also provided:

- Weekday flow = 1.24 (adjusting factor) * (3*AM + 6*PM + 3*PM)
- Weekend flow = 0.77 (adjusting factor) * (3*AM + 6*PM + 3*PM)

It was assumed 253 weekdays, and 112 weekend days per year. Thus,

- Annual traffic flow= 253* average weekday flow+112* average weekend flow.

### 4.2.2 **Emissions**

PITHEM (Namdeo and Goodman, 2012) was used to calculate emissions from road transport. The methodology and calculations behind the emissions estimates produced by this programme are described in detail in Sections 2.6 and 4.2.2. PITHEM contains an integral emission model which calculates emissions and particulates using latest UK emission factors (i.e. National Atmospheric Emissions Inventory (NAEI)). National fleet emissions factors are determined as a function of vehicle type, age, emission control standard, engine size and fuel used. PITHEM is currently under development to take into account updated NOx Emission Factors taken from the latest DEFRA Emission Factor Toolkit - Version 5.1.3. These factors are applied via PITHEM to the count and traffic speed data obtained for each modelled link. Emissions estimates were produced for each link in the cordoned TPM model (Figure 14).

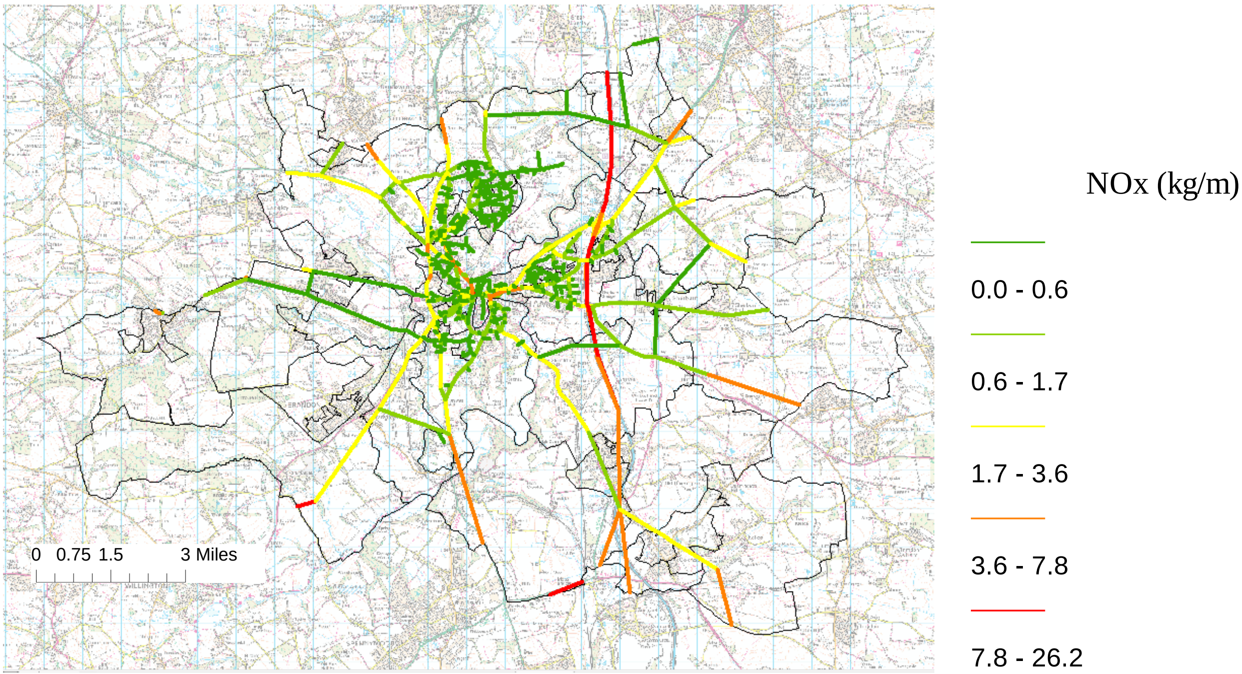





Figure 14. Major road network emissions in the City of Durham

AM, I\P and PM peak network speeds were used to calculate the average-speed for each link. Vehicle fleet compositions were developed according to the structure of PITHEM using data from the TPM model.

After discussion with DCC it was confirmed that no data existed regarding emissions from point or area sources in the area. Therefore, commercial and domestic contributions to local air pollution in Durham were obtained from DEFRA background map sector data (Table 15). This table provides details of the source components which were selected to comprise background emissions. This selection was made following guidance from DEFRA's Background Concentration Maps User Guide; and discussion with DCCs Air quality Officer, David Gribben (2012). The source sectors include transport, industry and commercial. The provision of individual sector data enables excluded sectors to be subtracted from the total background. "This approach reduces the risk of double counting pollutant concentrations by avoiding the inclusion of both the estimated background component and the detailed sector component being evaluated" (DEFRA, 2017a).

Table 15 Point or area source data (DEFRA, 2012a).

| DEFRA Header | Description |
|---|---|
| Industry_in_10 | Industry area in square sources (combustion in industry,<br><br>energy production, extraction of fossil fuel, and waste) |
| Industry_out_10 | Industry area out square sources (combustion in industry,<br><br>energy production, extraction of fossil fuel, and waste) |
| Domestic_in_10 | Domestic, institutional and commercial space heating in square sources |
| Domestic_out_10 | Domestic, institutional and commercial space heating out square sources |
| Aircraft_in_10 | Aircraft in square sources |
| Aircraft_out_10 | Aircraft out square sources |
| Rail_in_10 | Rail in square sources |
| Rail_out_10 | Rail out square sources |
| Other_in_10 | Other in square sources (ships, offroad and other emissions) |
| Other_out_10 | Other out square sources (ships, offroad and other emissions) |
| Point_Sources_10 | Point sources |

### 4.2.3 **ADMS-Urban**

Emissions were dispersed using the Gaussian Dispersion Model ADMS (CERC, 2006) (See Section 3.8.1). A review of Gaussian Dispersion Models was provided in this section. ADMS was identified as the most suitable program for this research due to the availability of licensing and widespread use by DCC (Durham County Council, 2016). The model set-up carried out in this work is documented in the following sections.

### 4.2.4 **Meteorological Data**

Meteorological data was obtained from an automatic weather station maintained by Durham University on behalf of the Met Office (UK's National Weather Service). Hourly data from 2010 was used in the modelling to match the traffic data base year. Meteorological data consisted of wind speed (m/s), wind direction ($^{o}$), temperature ($^{o}$C), precipitation rate (mm/h), relative humidity (%) and cloud cover (oktas).

Table 16 Meteorological data used in this modelling study
Source: Durham University, 2011

| **Data Name** | **Abbreviated name** | **Units** |
|---|---|---|
| Wind Speed | U | m/s |
| Wind Direction | PHI | Degrees |
| Temperature | T0C | $^{o}$C |
| Precipitation Rate | P | mm/hour |
| Relative Humidity | RHUM | % |
| Cloud Cover | CL | oktas |
| Hour | THOUR | - |
| Day | TDAY | - |
| Year | YEAR | - |

It is accepted that meteorological conditions vary at the micro and meso-scale (Vallero, 2008). However, meteorological data at this scale was not available for the study area. Therefore, whilst the use of single point meteorological data is not representative of the meteorological conditions throughout the area, it was considered the best available. Furthermore, the collection of additional meteorological data was neither financially nor practically feasible within the timescale of this research.

Table 17 and Table 18 provide a summary of the meteorological conditions for the city of Durham for the year 2010.

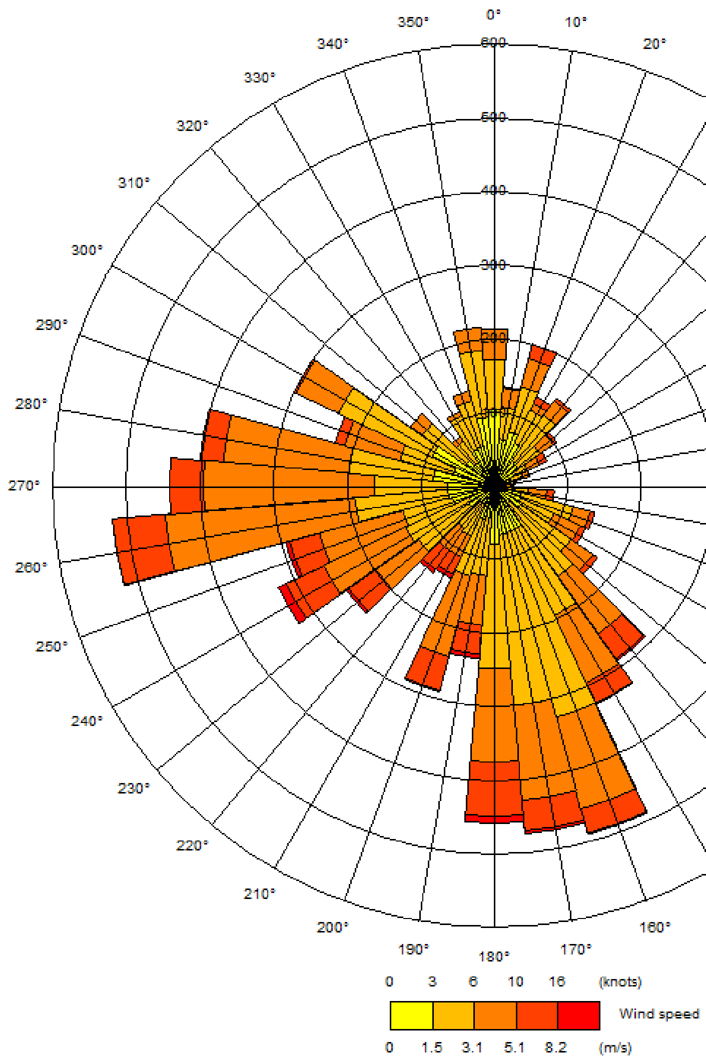
Table 17 Summary of meteorological conditions for the city of Durham for the year 2010

| | **Temperature ($^{o}$C)** | **Wind Speed (m/s)** | **Precipitation (mm/h)** | **Relative Humidity (%)** | **Cloud Cover (Oktas)** |
|---|---|---|---|---|---|
| **Average** | 10.14 | 2.62 | 0.08 | 80.23 | 3.76 |
| **Maximum** | 37.24 | 11.37 | 10.40 | 99.90 | 8 |
| **Minimum** | -6.00 | 0.00 | 0.00 | 0 | 0 |

Higher temperatures were observed between the months of April and August which corresponds to British Summer Time (BST). The maximum wind speed (11m/s) was recorded on 11$^{th}$ November at 23.00h. The highest precipitation rate occurred on 1$^{st}$ November at 19.00h. Finally, higher relative humidity and cloud cover values were observed between the months of August and March.

The prevailing wind was from the south-south west and east direction which influences the dispersal of emissions across the study area (Table 18). Prevailing wind can be observed as higher frequency wind directions over the observed time period have spokes with longer radial length (scale indicates hours in a year that the wind blows from that direction). The wind orientation is of particular significance when considering the layout of Durham's major road network as roads perpendicular to the prevailing wind are more likely to result in high pollution areas due to the effects of canyons (Section 2.8). Yearly data was analysed to investigate whether there was any significance in wind direction variation across the year or seasons. However, no specific pattern or distribution was identified. Wind speed is categorised into appropriate ranges and illustrated by colour for each directional spoke. 9% of the hourly sequential data exhibited wind speeds of ≤1m/s and 5% of the data exhibiting wind speeds of ≤0.75m/s. As discussed in Section 2.8 dispersion modelling performs poorly in calm conditions. However, the proportion of calm conditions presented in the data is relatively low and the majority of data can be successfully processed in subsequent model runs.

Table 18 Wind rose (wind speed and wind direction) for the city of Durham Year 2010




*Radial scale (hours)*

Dry deposition ($F_{dry}$) and wet deposition ($F_{wet}$) was applied in ADMS-Urban for this pilot. The requirement to take both processes into account in air quality modelling is identified in Section 2.8.1.

### 4.2.5 Background Data

The use of background data from a rural monitoring station is appropriate if all local sources are explicitly modelled (DEFRA, 2017a). Therefore, background data was obtained from rural monitoring stations for use in this investigation. Background concentrations from two background monitoring sites, namely Byland Lodge and McNally Place were selected for $NO_2$ and NOx for 2010. These background sites were considered the most appropriate option for use in this research due to their location within the study area and their use in statutory air quality modelling by Durham County Council, for example, Air Quality Progress Report, Durham County Council, 2010a.

Although the background data from the two identified sites met the requirements of ADMS-Urban, only annual mean concentrations were available. The absence of hourly data restricted some of the evaluation statistics which could be applied to the modelling (CERC, 2006).

### 4.2.6 Chemical Reaction Scheme

ADMS-Urban contains a chemical reaction scheme known as The Generic Reaction Set (GRS) scheme that addresses a series of chemical reactions which define NOx chemistry. Inputs of NOx, $NO_2$ and $O_3$ background concentrations are required prior to modelling this chemistry. The GRS takes into account eight chemical reactions and as such does not extend to include all the chemical reactions that take place in the atmosphere (CERC, 2006).

Two separate chemistry modules within ADMS-Urban make use of the GRS. The simpler of the two modules assumes no spatial variation in the background pollutant levels. However, the Chemical Reaction Scheme with Trajectory (CRST) model takes spatial variation into account through the use of a Lagrangian box model (CERC, 2006).

The CRST was selected in this investigation to allow for spatial variability in photochemical reactions. The module aggregates the emissions, meteorological conditions and deposition rates into 5km x 5km grid squares and then calculates local pollutant concentrations using the GRS.

### 4.2.7 Grids and Specified Points

To model spatial variation point, area and road emissions, sources were aggregated to a grid source (200m x 200m resolution). Whilst a smaller grid size could potentially enhance the accuracy of the results, the grid size was deemed appropriate for this meso-scale study due to the increase in run times associated with finer resolution grids. A much higher resolution grid output was explored for the micro-scale Durham study described in Chapter 6. ‘Specified Points’ were also selected in the modelling to allow for outputs at monitoring stations (CERC, 2006).

### 4.2.8 Health and Environmental Justice Modelling

HES data has been obtained from the North East Public Health Observatory (NEPHO) (See Section 2.10). Suitable ICD codes were selected so that respiratory and circulatory illness could be accurately represented in accordance with COMEAP. Health parameters reported on include respiratory associated illnesses including asthma (COMEAP, 2010; COMEAP, 2013; COMEAP, 2015). Specific references relevant to the selected illnesses are detailed in Section 5.2.3.

All data was output at LSOA level. Further segmentation of the data, for example by age, was avoided to reduce data suppression. As the City of Durham AQMA was declared based on continued $NO_2$ exceedance and research suggests that $NO_2$’s primary health impact is adverse respiratory effects, the results of respiratory admissions are reported in this research (COMEAP, 2010; COMEAP, 2013; COMEAP, 2015).

Despite assistance and support from NEPHO, the sensitivities around an individual’s health did lead to limitations in the data provided. In order to protect anonymity it was not possible to obtain individual or household data. Even at LSOA level the data provided does not represent actual admission rates, given that in instances where admission rates are low for a particular illness, the actual figure is supressed so as to protect anonymity. Whilst still significant, admission rates for respiratory illness are generally fairly low in the UK, accounting for 5% of hospital admissions in 2011 (British Lung Foundation, 2018).

Therefore, it is anticipated that data suppression will have had an impact on subsequent total admission rates, and it is assumed that rates across all hospital admissions differ slightly from reality. However, whilst this limits some of the potential statistical methods that could be used to analyse the results, overall the data provides a valid understanding of health both in, and relative to, other LSOAs. Moreover, in the context of an EJ study the effect of data suppression, whilst unquantifiable, is not deemed significant where HES data has been used (e.g. Gilmore, 2011).

Finally, the IMD data have been used as a general measure of social deprivation in this study (See Section 2.9). To summarise, the IMD were developed by the Social Disadvantage Research Centre at the University of Oxford, using 38 indicators which have been divided into 7 weighted domains including measures of income; employment; mortality; education; housing; crime; and living environment (ONS, 2010). This index is available to download for each Lower Super Output Area (LSOA) from the Office of National Statistics. Data available includes the IMD score, rank of Index of IMD, and the individual score and rank of each domain with the IMD. For this investigation, results from the 2010 IMD are reported as these figures are most relevant for the air quality modelling base year of 2010.

As with the available health data, the use of IMD data in the research provided limitations for the research. Firstly, in terms of scale, the use of LSOA area data in the pilot study was largely determined by the availability of suitable deprivation data. This limitation is discussed further in Section 4.4.2 and stems from the fact that each LSOA has a minimum population of 1000, and a mean population of 1500. In contrast, Durham's AQMA covers a residential population of approximately 750. This makes obtaining a detailed understanding of the relative deprivation of those households subject to the very highest levels of air pollution in Durham impossible using this process and data source.

## 4.3 Results

### 4.3.1 Air Quality Results

The evaluation of the model performance against observed monitored data is discussed in detail Section 5.2.2.2. The model evaluation is discussed in the context of a comparison between the relative performance of the meso-scale pilot model described in this chapter, and an alternative model derived from micro-scale emissions inputs discussed in Chapter 5. Both models are then compared against observed data. Thereby, the meso-scale model performance and evaluation is not discussed in any detail in this chapter.

To summarise the findings, an analysis of fractional bias (FB) using the methodology of Chang and Hanna (2005) found that FB values were within a factor of two of the observed, indicating no systematic under or over-prediction for the model. FB is a measure of mean bias. It indicates the mean under or over-prediction and is calculated according to the below equation:

$$FB = \frac{(\overline{C_o} - \overline{C_p})}{0.5(\overline{C_o} + \overline{C_p})}$$

Where $C_o$ denotes the observed concentration values, and $C_p$ denotes predicted concentration values ($\bar{C}$ denotes the average of the data set). FB ranges from -2 (extreme over-prediction) to +2 (extreme under-prediction) with a perfect model having an FB of zero. FB is based on a linear scale and the systematic bias refers to the arithmetic difference between $C_p$ and $C_o$. (Chang and Hanna, 2005).

Furthermore, a review of the spatial distribution of air quality across the study area reveals a distinct pattern of high $NO_2$ levels within the central City of Durham urban zone. This is consistent with smaller scale modelling produced by DCC during work completed prior to the declaration of an AQMA (Durham County Council, 2007).

### 4.3.2 Relationship between deprivation and health

The existence of a complex relationship between deprivation and health is well documented in the literature review, Section 2.5.1. Prior to a review of the spatial distribution of Durham's air quality, it is important to consider the base line make up of Durham's deprivation standings relative to the wider area of England. Additionally, the relationship between deprivation and health data in Durham has been considered to provide further local context.

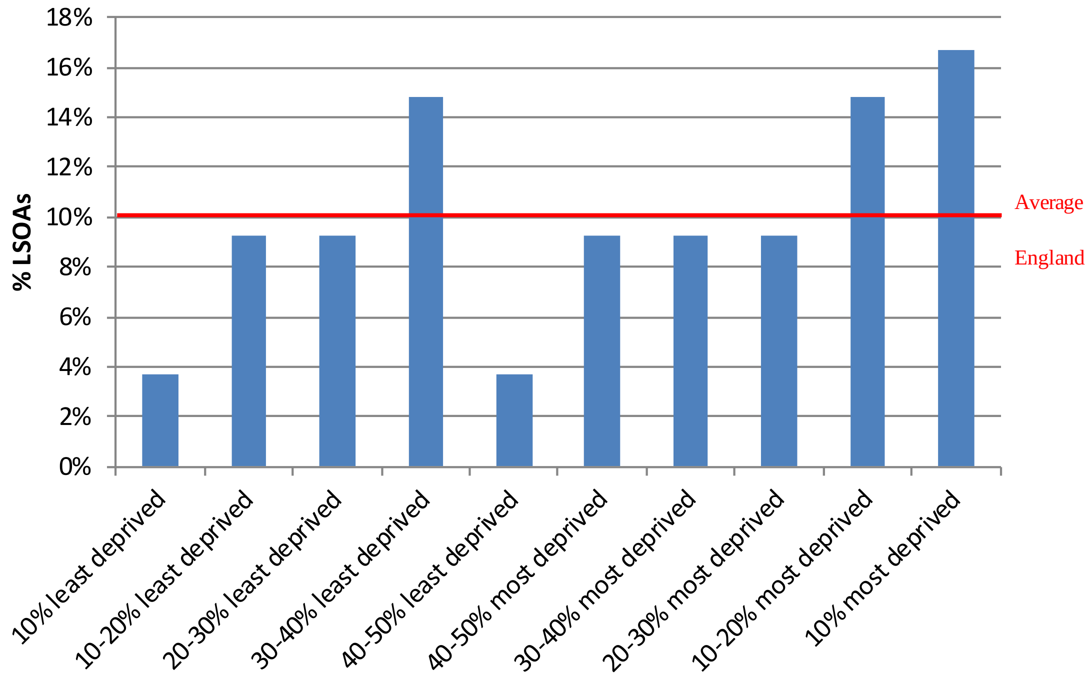



Figure 15. Percentage of City of Durham LSOAs in each national deprivation decile

Generally, Durham has a broad mix of both affluent and more deprived areas. Figure 15 shows the percentage of City of Durham LSOAs in each national deprivation decile. The City of Durham comprises 54 LSOAs. The single most represented decile is the '10% most deprived' indicating a substantial presence of deprived areas within the study boundary. However, there is strong representation across the deciles and overall 41% of City of Durham LSOAs fall in the 50% least deprived deciles. This indicates that the area as a whole contains a broad range of deprivation levels relative to the rest of the UK.

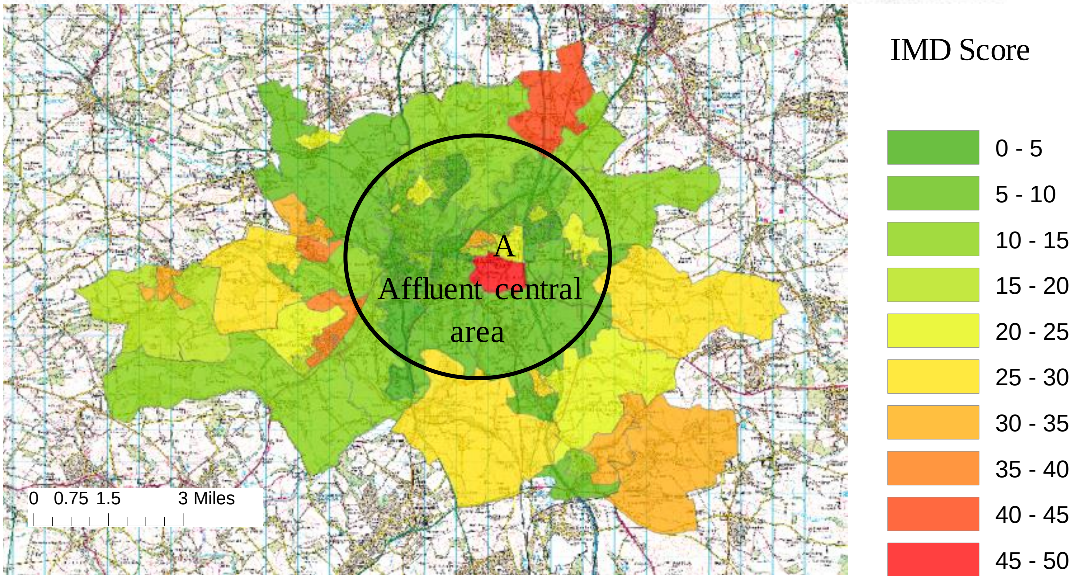



Figure 16. Indices of Multiple Deprivation Score for the City of Durham (LSOA)

Figure 16 shows the IMD score mapped spatially for the City of Durham. Overall a pattern of a least deprived central area and a more deprived peripheral area is apparent. However, the single most deprived LSOA is contained within this central area ('A' Figure 16).

The City of Durham AQMA was declared based on continued exceedance of $NO_2$ objectives. As discussed in Section 2.3, research suggests that $NO_2$'s primary health impact is adverse respiratory effects (COMEAP, 2010; COMEAP, 2013; COMEAP, 2015) (See also **Appendix A**). Therefore, respiratory admission data was investigated in this meso-scale study in order to determine if a relationship between deprivation and health was evident across the City of Durham.

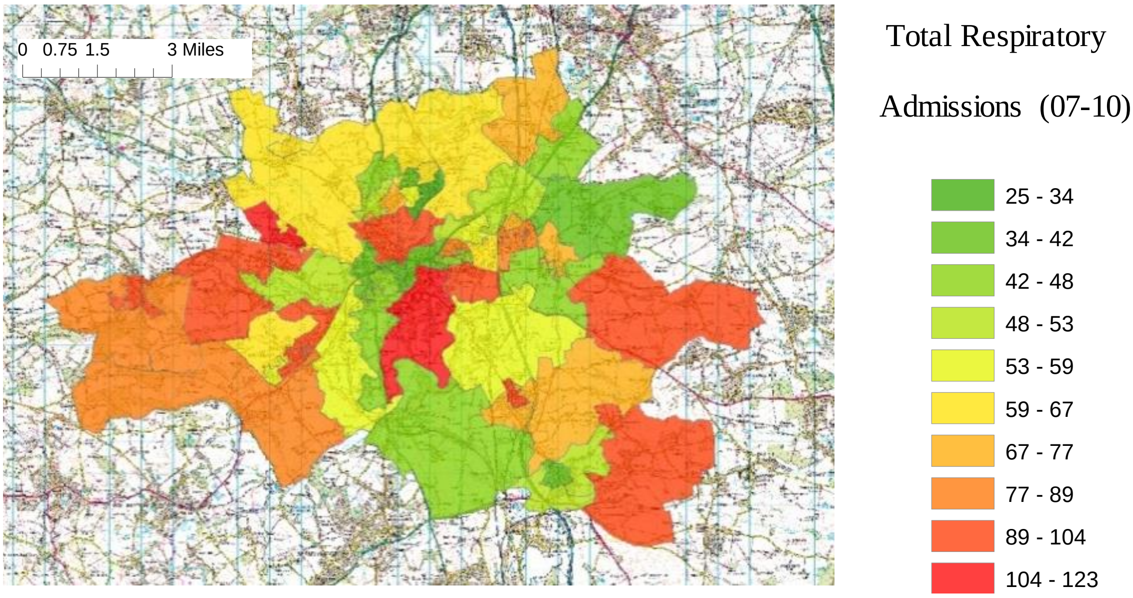





Figure 17. Number of respiratory hospital admissions for the City of Durham (LSOA)

Figure 17 shows the spatial distribution of total respiratory hospital admissions for the City of Durham from 2007 to 2010. No succinct visual spatial pattern is evident in the results. The highest total admissions were recorded in two LSOAs within the central City of Durham area. The least number of admissions were recorded in two adjacent LSOAs approximately 2km north of Durham City centre.

The lack of an identifiable pattern in the results is perhaps not surprising given that is recognised that there are an almost infinite set of circumstances that lead to an admission in to hospital. Nonetheless this type of analysis is valid and of interest, for example, at the UK scale by Mitchell and Dorling (2003), and Mitchell et al. (2015) and a number of other studies detailed in Chapter 2, Table 1 in which LSOA hospital admissions data is reviewed.

Considering respiratory illness, external factors such as environment are an acknowledged and serious contribution to respiratory health (Unger and Bogaert, 2017). However, as discussed in Section 2.5, the mechanisms that lead to respiratory illness are vast, from early interactions between infectious agents such as viruses, bacterial infections, to an individual's composition of the respiratory microbiome (Unger and Bogaert, 2017). In combination with individual general health, lifestyle choices such as prevalence of smoking, and general population demographics including age and gender, the number of potential confounding factors of consideration is significantly beyond what could reasonably be expected to be explored; and the prevalence of suitable data is a substantial limitation should such work ever be attempted. Furthermore, despite significant advances in medicinal research and understanding of respiratory illness, there are still significant knowledge gaps in understanding cause and effect. For example, the importance of other underlining health issues, including mental health, has only recently been understood as individuals with mental illness have an increased risk of a wide range of illness including respiratory disease (Chadwick, 2018).

As discussed in Section 2.5.2, it must be noted that it is not proposed to investigate the causal factors behind the data. Such a study, if achievable in any capacity, falls significantly beyond the scope of this project. Instead, in keeping with the majority of work in the field of EJ, the challenge is to identify and understand links between the themes so as to highlight injustices and consider strategies which may resolve them.

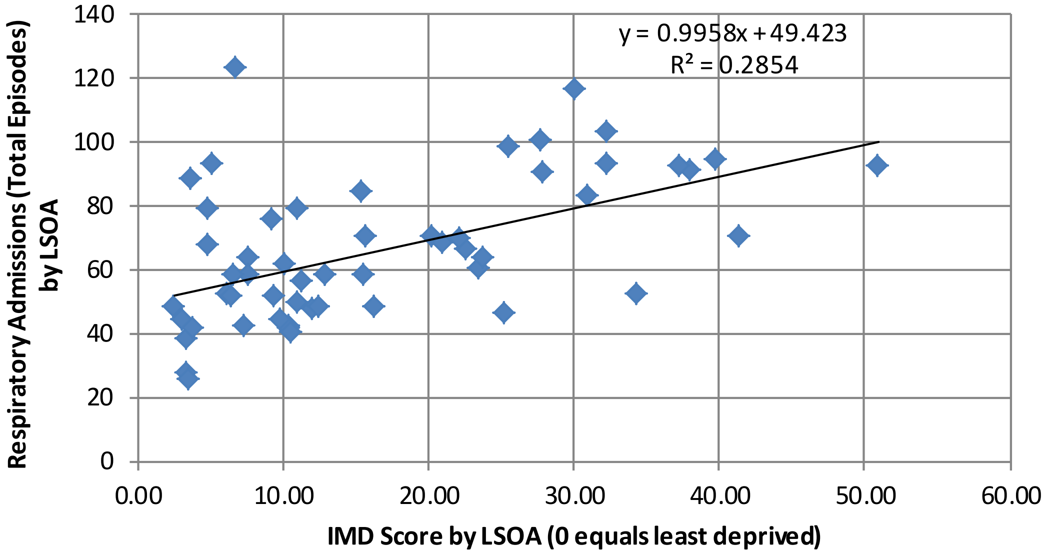



Figure 18. Relationship between deprivation (IMD) and health (respiratory admissions) in Durham.

A scatter plot of deprivation and respiratory admissions shows the relationship between the two themes (Figure 18). Using simple linear regression it is evident that there is a positive relationship between the variables, although an $R^2$ value of 0.29 suggests this relationship is not particularly strong. These findings are similar to those reported in other studies (See Namdeo and Stringer, 2008). As discussed earlier in this section and in work such as Namdeo and Stringer (2008) the prevalence of low $R^2$ values is largely expected given the multitude of confounding factors that influence an individual's personal health.

### 4.3.3 Relationship between air quality, deprivation and health

Following the modelling framework outlined in Section 4.2, mean modelled $NO_2$ outputs for each of the City of Durham's LSOAs were paired with corresponding deprivation and health data. Analysis of these datasets allowed the EJ of the spatial distribution of City of Durham's air quality to be identified.

Scatter plots were produced to show the interrelationships between each of the themes (Figure 19 and Figure 20). The $R^2$ values from the resultant scatter plots have been summarised in Table 19. Linear regression was used, not to infer causality between the variables, instead to test for an association between them.

The application of linear regression was deemed appropriate following a review of the methodologies adopted by King and Stedman 2000; Pye et al. 2001, 2010; Linares et al. 2004; and Namdeo and Stringer 2008.

King and Stedman (2000) used linear regression to identify a general positive correlation between $PM_{10}$ and the Department of the Environment, Transport and the Regions (DETR) Index of Local Deprivation 1998; and $NO_2$ and the DETR Index of Local Deprivation 1998 in London, Belfast and Birmingham.

Similarly, Pye et al (2001) found evidence of a positive correlation between $NO_2$ and $PM_{10}$, and social deprivation (utilising the Index of Deprivation) for Greater London, Birmingham City District and Greater Belfast using linear regression. In 2010 this work was revisited using updated social deprivation statistics, and the same application of linear regression. Again, a positive correlation between air quality and social deprivation was identified.

Linares et al 2004 used linear regression to analyse the effects of the principal urban pollutants ($PM_{10}$, $O_3$, $SO_2$, $NO_2$, and NOx) on daily emergency hospital admissions of children less than ten years of age in Madrid, their findings indicated that the strongest association was with $PM_{10}$.

Finally, Namdeo and Stringer used (2008) UK Census 2001 data to derive indicators of health and deprivation levels of the population in a study area in Leeds. Cumulative deprivation index (CDI) and Cumulative Health Index (CHI) scores were plotted on a scatter plot and linear regression used to identify that social deprivation and health are strongly related in Leeds.

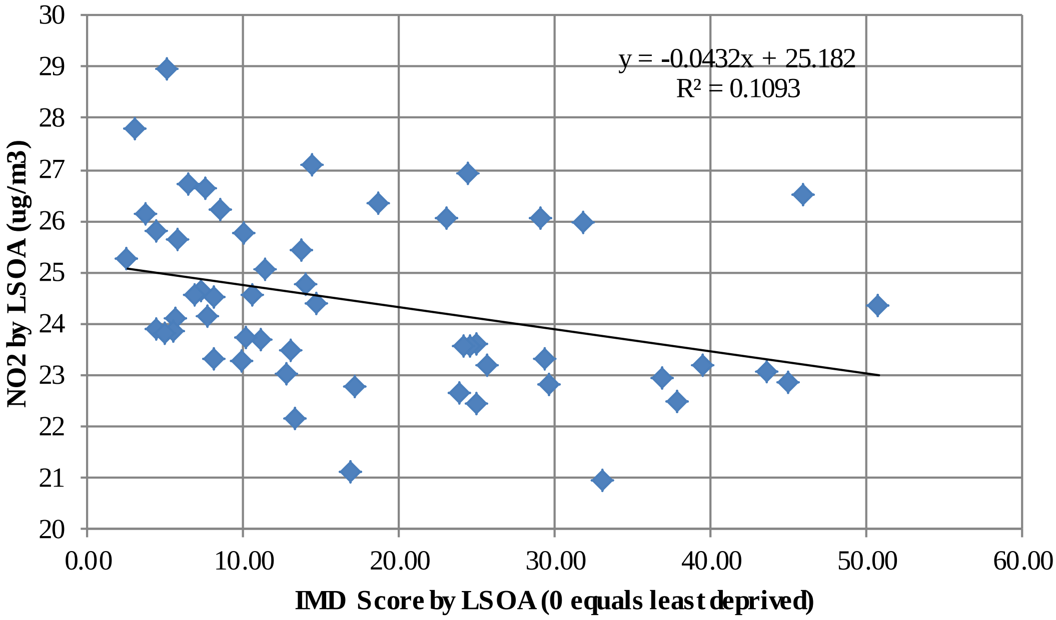



Figure 19. Relationship between deprivation (IMD) and Air Quality ($NO_2$) in Durham.

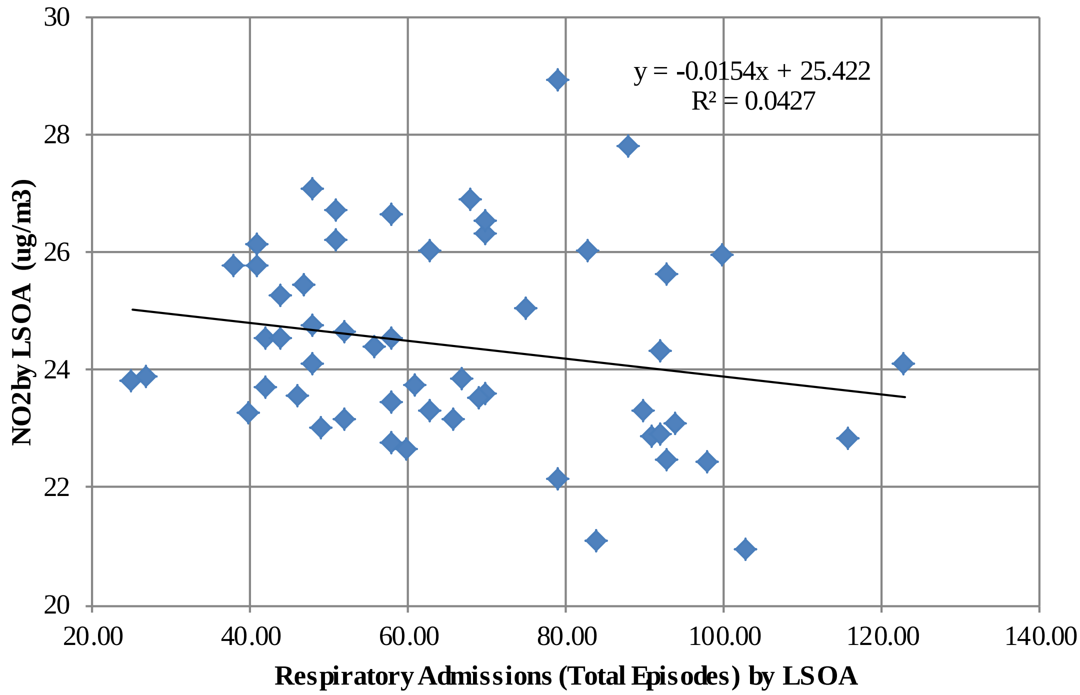



Figure 20. Relationship between health (respiratory admissions) and Air Quality ($NO_2$) in Durham.

No relationship was identified between either air quality and deprivation, or air quality and health using this technique. The fact both $R^2$ values were negative for these relationships suggest a negative relationship between both air quality and health and air quality and deprivation. However, the low $R^2$ values imply a low percentage of deviation can be explained by these relationships.

Table 19 $R^2$ values from scatter plots of the research themes

| | **Deprivation** | **Air Quality** |
|---|---|---|
| **Deprivation** | | **0.1093** |
| **Health** | **0.2854** | **0.0427** |

Quartile analysis was also conducted to investigate the relationship between the variables. The results show that the least deprived group (first quartile of deprivation index) experience higher $NO_2$ concentrations compared to the most deprived group (third quartile of deprivation index) (Table 20). These findings are in keeping with the slope and $R^2$ values and again imply a negative relationship between air quality and deprivation.

These findings contradict those found by Mitchell and Dorling, 2003 and Namdeo and Stringer, 2008. However, similar findings have been identified previously. For example, King and Stedman (2000) found that whilst London, Birmingham and Belfast had higher concentrations of air pollutants in areas of greater social deprivation, Cardiff City did not appear to display any obvious correlation.

Table 20 $NO_2$ and quartiles of deprivation and health

| Quartile | Deprivation (IMD score) | Health (Respiratory Admissions) | Average of corresponding $NO_2$ values ($\mu g/m^3$) | SD |
|---|---|---|---|---|
| First quartile (25th percentile) | 7.53 | 48 | 25.45 | 1.54 |
| Second quartile (50th percentile) | 13.57 | 62 | 24.24 | 1.24 |
| Third quartile (75th percentile) | 25.20 | 85 | 24.31 | 1.77 |

A surface plot of the results shows evidence of nonlinearity of the relationship between the variables (Figure 21). Two distinct peaks are observed showing high $NO_2$ and close to average respiratory admissions at both ends of the deprivation scale (# and ~).

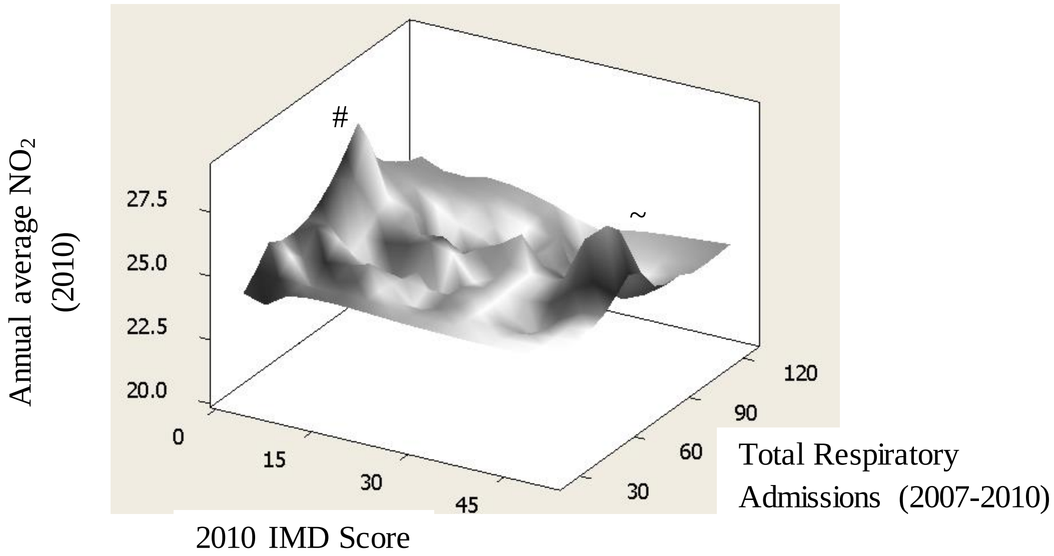



Figure 21. Surface plot of deprivation, health and average $NO_2$

The deprivation, health and air quality surface plot (Figure 21) provides strong evidence that the relationships between the themes are non-linear. Furthermore, the constant (error component) of a number of the regression equations is also relatively high. A review of alternative approaches on applied to similar data and studies revealed the potential to apply other models to the data, for example, Poisson Regression (e.g. Schwartz, 1996); multiple linear regression (e.g. Wang and Chau, 2013); and multivariate regression (e.g. Walters, 1995). The principle reason of adopting a nonlinear approach is to address the high number of variables that are likely present in the data. One of the key variables included in the aforementioned studies are weather variables such as mean temperature, and mean humidity, given the impact of weather on common respiratory conditions such as asthma (Tosca et al, 2014). Other variables likely to be present in the data and cited as independent variables in similar studies include information on seasonal influenza epidemics, season of admissions and sex and age groups (Wang and Chau, 2013).

However, whilst it is acknowledged that there is scope for additional statistical analysis in the pilot study, a number of considerations led to the research developing in the direction of a microscale study, utilising a revised dataset, for the subsequent research.

Firstly, the importance of scale in the findings. Namely, the use of LSOA level data in Durham leads to significant weaknesses as a result of the population size within a single LSOA (1500 mean number of residents), in relation to the physical size of the study area (52 LSOA's), and particularly, the number of households identified as suffering exceedances in air quality targets (44 households). The impact of scale is discussed at length in Chapter 5 and 7. These factors would limit the strength of further statistical analysis; and draw questions to the suitability of such work.

Finally, the availability of health data suitable for use in a primarily geographical based research project. The majority of the cited studies exploring links between air quality and health using Poisson Regression or similar techniques have access to large health datasets devoid of specific patient address information. This type of data is readily available from appropriate institutions; and can be used in conduction with generalised air quality information, often at the city level, to explore links between the themes. However, given that this study is primarily focused on EJ and the spatial distribution of air quality, more specific patient address data was required in order to explore the spatial variations in the themes. This limits data availability due to data protection conflicts.

Nonetheless, despite the recognised limitation of restricting the exploration of the pilot study data to an investigation of linear relationships, it was felt that the inclusion of linear regression analysis in the pilot was valuable. This is as the identified weak relationships provided justification that further study was warranted, albeit at a more appropriate scale.

## 4.4 Discussion

### 4.4.1 EJ in City of Durham

There is no evidence of environmental injustice in the distribution of air quality in the City of Durham at the meso-scale. Furthermore, whilst no linear relationship is evident, a review of the spatial patterns and quartiles of deprivation, health and air quality revealed some evidence of an inverse relationship. Some central Durham areas showed the lowest levels of deprivation, yet poor health and the poorest modelled air quality. In contrast a weak relationship between health and deprivation has been identified in City of Durham.

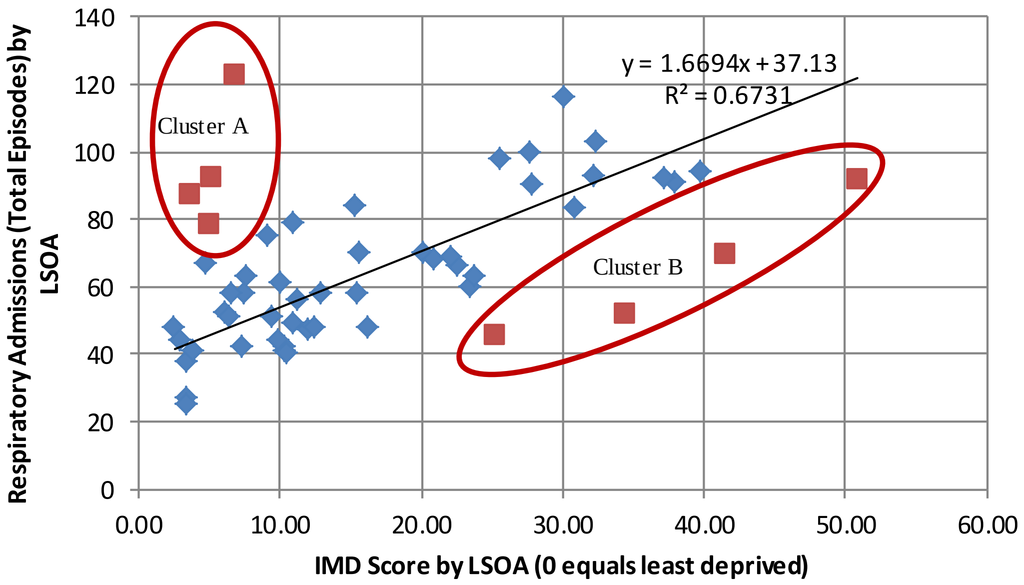



Figure 22. Relationship between deprivation (IMD) and health (respiratory admissions)

Additionally, evidence of clustering can be seen in the results. For example, a potential cluster of low deprivation, poor health LSOAs has been identified in Figure 22, indicated by the red points at the top left of the graph. A second cluster group has also been identified in the bottom right of Figure 22. These data points represent LSOAs with lower respiratory admissions for their respective deprivation scores than appears to fit the general trend.

Furthermore, when the identified clusters are viewed spatially, it is evident that this clustering has an apparent spatial dimension (Figure 23). Cluster A, within the central area of the City of Durham study area could be characterised as an area of affluent central Durham, where health is poor and air quality relatively low. In contrast, cluster B represents an opposing cluster of deprived, healthy areas in more peripheral locations.

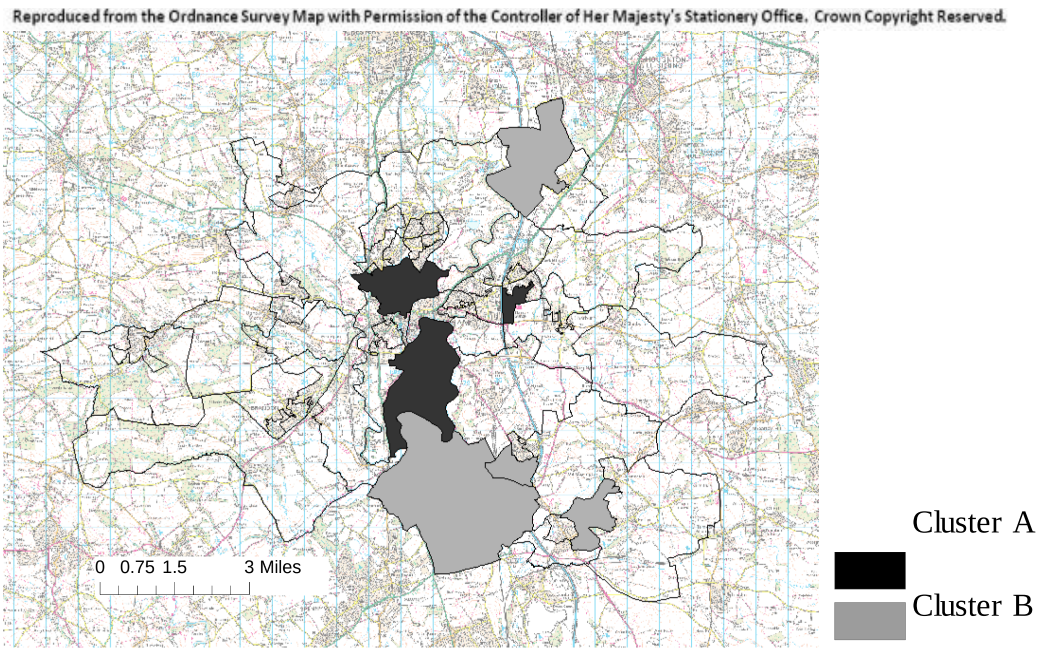



Figure 23. Spatial clustering in City of Durham

A final consideration is the existence of confounding factors which may be influencing the results in a number of ways (Walker, 1992). Additionally, the impact of personal exposure to varying levels of air quality has an influence on health beyond an individual's residential LSOA (Section 2.11). The issue of confounding factors is discussed in Section 2.5.2.

### 4.4.2 **Limitations of Approach**

The accuracy of the air quality modelling used in this meso-scale pilot satisfies the recognised standard set of statistics under the European Initiative on Harmonisation within Atmospheric Dispersion Modelling for Regulatory Purposes (Chang and Hanna, 2005). However, it is recognised that this accuracy could be improved further. Traditionally, fuel consumption and hence vehicle emissions, have been estimated by relating average vehicle speeds to fuel consumed per kilometre at that average speed. This is based on simple relationship “u-shaped” curve and is suitable for producing high level estimates in a strategic context (Walter, 1995). Furthermore, this methodology fails to account for “congestion” emissions from stop-start traffic where fuel consumption and emissions will typically be higher. This is a particularly significant omission as congested traffic is the major source of emissions in AQMAs (Chatterton, 2008).

The use of IEMs is explored in Chapter 5 to provide a more accurate estimation of traffic emissions in Durham at the micro-scale.

Spatial scale has also emerged as a substantive limitation of this meso-scale study. Firstly, the size of the geodemographic boundary area is acknowledged to have a considerable impact on the results outcome of an EJ study. For example, the IMD, used to characterise deprivation in this study is available at the LSOA level. However, LSOAs cover a minimum population of 1000, and a mean population of 1500. In contrast, Durham’s AQMA covers a residential population of approximately 750. Furthermore, according to the 2010 Detail Air Quality Assessment completed by DCC only 44 households in Durham are identified as being exposed to $NO_2$ concentrations above 40µg/m$^3$ (Durham County Council, 2010a). Thereby, it is reasonable to conclude that LSOAs cover too large a population area to provide sufficient spatial detail for investigating relationships between deprivation and air quality. However, IMD is widely used in EJ studies and air quality analysis research (See Table 1, Section 2.5.3). Secondly, the study area identified in this meso-scale study represents 54 LSOAs. This sample size limits the relevant statistical techniques which could be applied in this study (Walker, 2005).

As discussed, a more detailed micro-scale study of Durham described in Chapter 5 and 6 addresses some of the issues of spatial scale by using household level air quality and geodemographic data. Furthermore, the micro-scale study provides a more detailed platform to explore the impact of results across spatial scales (e.g. household, postcode and LSOA).

### 4.5 Summary

This chapter has documented the successful application of the modelling framework described in Chapter 3 at the meso-scale. The pilot, based in the City of Durham, provides assurance on the suitability of the framework for investigating the research themes identified in previous chapters. Furthermore, the pilot has identified limitations which will be addressed in a more detailed micro-scale assessment of EJ presented in Chapters 5 and 6.

Moreover, an understanding of the EJ of the spatial distribution of air quality across Durham has been established at the meso-scale. No evidence of environmental injustice has been identified using linear evaluation. There is some evidence of spatial clustering in the results, including affluent central areas, where health is poor and air quality relatively low; and deprived, healthy areas in more peripheral locations. The meso-scale nature of the geodemographic data used in this study ensures further investigation into these findings should be conducted at the micro-scale. Therefore, a more detailed micro-scale study was conducted and is presented in the following chapters.

Health has emerged as an important driver for air quality policy (DOH, 2010). Research which establishes links between air quality, health and deprivation will enable a new emphasis on the importance of sustainable policy. This research highlights the complexity of these relationships and the significance of spatial scale and local variation on any understanding of them. It is hoped renewed understanding of this relationship and EJ concepts can aid step change in human behaviour, required if current sustainable policy aspirations are to be realised (Xenias, 2013).

CHAPTER 5

# 5. Air Quality, Health and Environmental Justice

## 5.1 Introduction

The findings in Chapter 4 built upon the understanding that there is a complex relationship between air quality, health and EJ.

Reflecting on the current literature and building upon the previous outcomes, this phase of the research aims to provide a comprehensive EJ assessment of air quality in the North East through two distinct studies. Firstly, to improve understanding of local level interactions, a fine spatial resolution case study has been conducted centred on the City of Durham. Therefore, a nested modelling approach has been adopted to allow the EJ investigation to be conducted across scales. The micro-scale study will address some of the shortcomings of a meso-scale study by addressing issues of scale and air quality model performance. Secondly, to compare and contrast findings from the studies in the City of Durham, two further meso-scale studies of Newcastle upon Tyne and Gateshead will provide insight into the EJ of these areas, as well as determine the suitability of the modelling framework in different areas within the North East of England.

Whilst the EJ studies of Newcastle upon Tyne and Gateshead have been defined as 'meso-scale' due to the size of the study areas, significant care has been taken to ensure the limitations identified in the City of Durham meso-scale trial described in Chapter 4 are mitigated. Therefore, despite the large study areas, fine postcode level geodemographic data has been used to enable a more comprehensive analysis of EJ at a scale better suited to the spatial variation of air quality within the city boundaries.

## 5.2 Micro-scale Durham Environmental Justice Study

Further to the meso-scale EJ study of the City of Durham described in Chapter 4 a micro-scale assessment has been completed. This will shed light on the extent to which population groups across the area studied are equally likely to be exposed to the largely traffic related air pollution created by the public's need for travel associated with goods, services, leisure and work (See Section 2.2 for discussion on the role of transport in air quality).

The key objectives of the micro-scale study are as follows:

- To challenge and further explore the findings of the meso-scale study, which found no significant environmental injustice in the spatial distribution of Durham's air quality;
- To test the application of the modelling framework at a finer spatial scale, and address some of the highlighted limitations of analysing EJ at a typical meso-scale level;
- To determine whether the use of an IEM to calculate transport emissions as an input for air quality dispersion modelling has the potential to improve the performance of the dispersion modelling when measured against monitored data, and thereby increase the accuracy of the EJ assessment;
- To investigate EJ using geodemographic data based on customer profiling in order to gain insight in to apparent spatial clustering of the EJ results in Durham. This represents an alternative approach to many EJ studies which traditionally use linear deprivation indices (See Section 3.3).

### 5.2.1 **Methodology**

The modelling structure presented in Chapter 3, Figure 3 has been expanded below to provide details of the modelling and data packages adopted for the micro-scale Durham study (Figure 24).

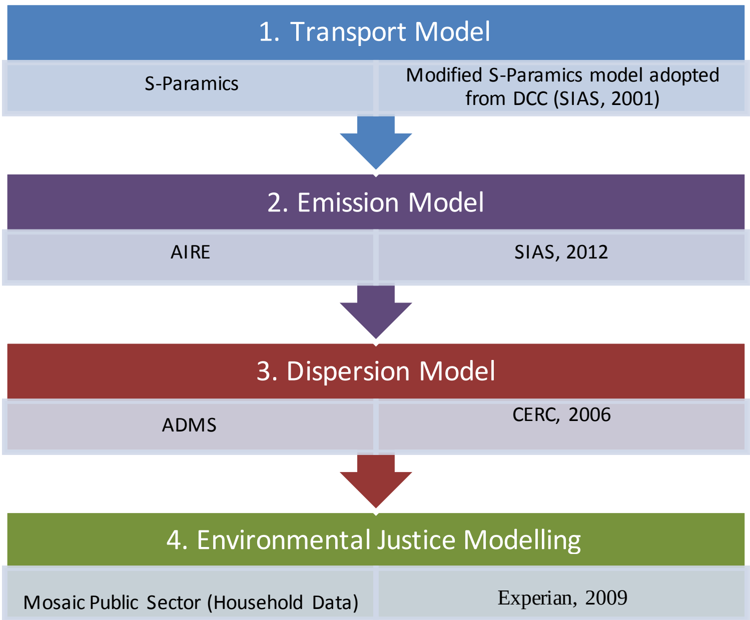



Figure 24. Micro-scale Durham Modelling Methodology

The traffic data used in this micro-scale research was derived from an S-Paramics microsimulation model (SIAS, 2001). Details of this model, the required amendments to ensure its suitability for providing data for emissions modelling, and the calibration and validation process undertaken to ensure reliability of results can be found in Sections 3.4 and 3.5.



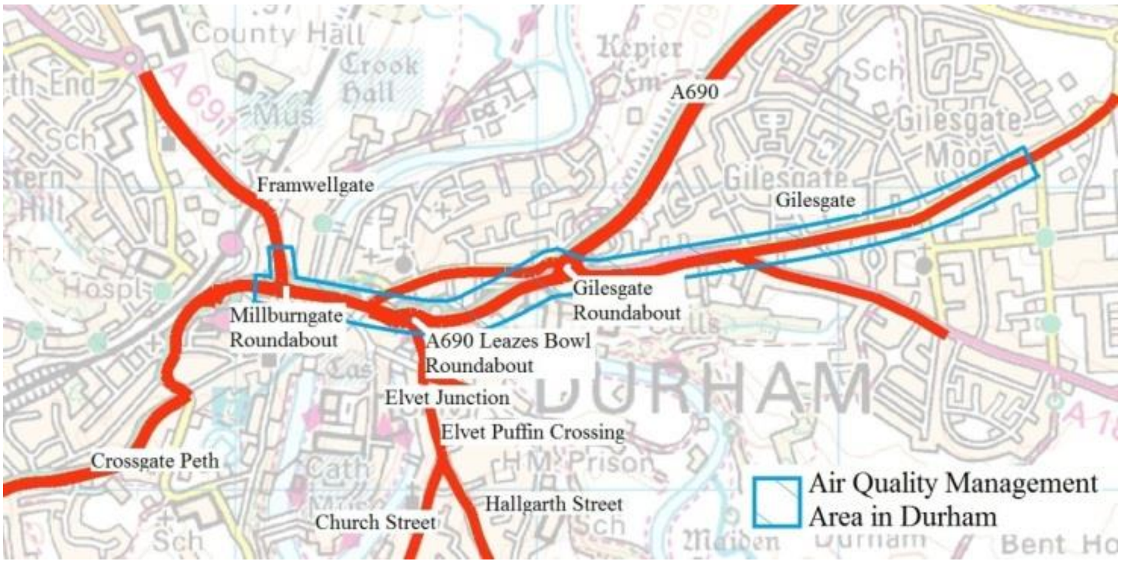


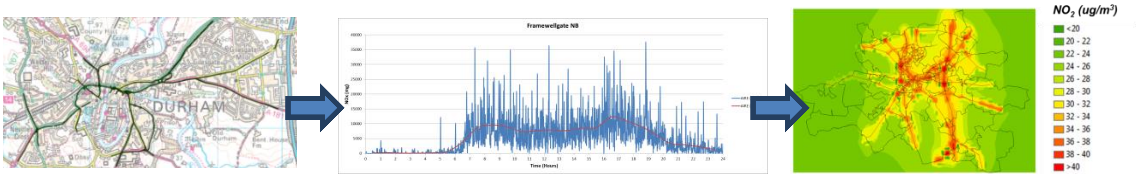

Figure 25. S-Paramics microsimulation model extents

The Paramics model was cordoned within the emissions program to reflect the size and shape of Durham centre. After the cordon process a total of 592 links were present in the modelled network (Figure 25). This cordon represents a 4.0x2.5 $km^2$ area of Durham, significantly smaller than the area covered in the meso-scale study described in Chapter 4. In summary it encompasses Durham's AQMA in its entirety and the majority of central Durham, including approximately 7500 residential properties.

The IEM, AIRE (SIAS, 2012) was used to calculate emissions from road transport. The methodology and calculations behind the emissions estimates produced by this programme are described in detail in Section 2.7.1, along with discussion on how this method has the potential to provide more accurate results than traditional average speed and flow based emissions estimates. Additionally, an exercise comparing the emissions results obtained using AIRE, with those obtained using the traditional average speed, average flow based method is presented in the following section. As discussed in

Chapter 4 no significant emissions from point or area sources were present in the area (See Section 4.2).

The emissions were dispersed using the Gaussian Dispersion Model ADMS following the same procedure as for the Durham meso-scale study (CERC, 2006). Similarly, identical meteorological and background data was applied in the modelling. Finally, the same chemical reaction scheme settings were selected (Section 4.2.6) (Figure 26).




***24-hour microsimulation*** ***Analysis of IEM Emissions results*** ***Air Quality Modelling***

Figure 26. Outline of approach to modelling road networks.

The selection of ‘Specified Points’ in the modelling allowed for air quality concentration outputs at monitoring stations, and enabled the comparison of results between this study and the meso-scale outputs discussed in the following section. Furthermore, ‘Specified Points’ were also used to output air quality concentrations for 7500 residential property addresses examined in the EJ assessment for this chapter (Figure 27). For illustrative purposes the variation point, area and road emissions sources were also aggregated to a shallow grid source (50m x 50m resolution). Whilst this high resolution grid significantly increased run time, it remained acceptable due to the reduced size of the network when compared to the meso-scale study.

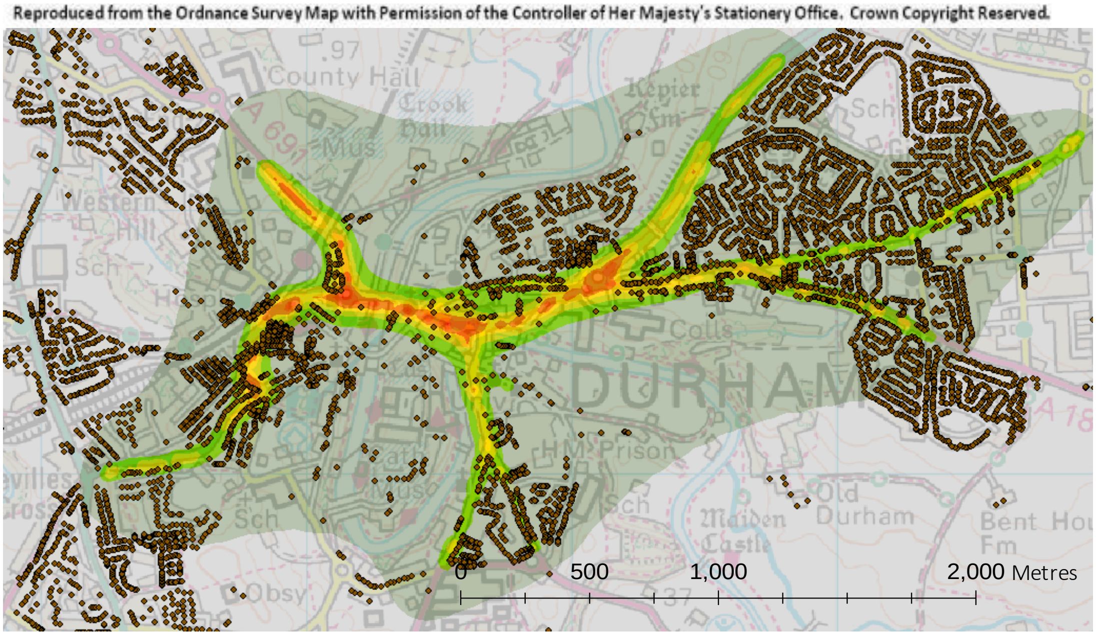



Figure 27. Location of 7471 residential property addresses in Durham study area

To complement micro-scale air quality modelling, household geodemographic data was obtained from Experian's Public Sector Mosaic database (Section 2.10). Household level Mosaic data was geocoded using OS Address-Point to provide coordinate information for every address in the Durham study area.

Geodemographic classifications provide a tried and tested means of measuring and monitoring small area conditions. They provide an accurate understanding of each citizen's demographics, lifestyles and behaviours by accessing a wealth of information on all UK individuals using more than 440 data elements (Experian, 2009). 62% of the data used comes from Experian's Consumer dynamics database, which sources information from a variety of databases including the electoral roll, credit and car ownership reports, the shareholders register, house sale prices and council tax bands. The remaining 38% of the data is sourced from Experian's current year estimates of the 2001 census (Experian, 2009).

Mosaic is based on analysis of the latest trends in UK society, a wealth of high quality, comprehensive data sources and a sophisticated proprietary approach to cluster analysis, supported by analysis of market research to validate the classification. Public Sector Mosaic customer profiling classifies all UK citizens into 15 groups (A to O) and 69 types (A01 to O69). Thereby, Mosaic analysis provides a sharper definition of deprivation than can be obtained by using the Indices of Deprivation alone (Bhatt, 2013).

Mosaic also contains health data within its demographic data element and is commonly used by health professionals (Gilmore, 2011). Specifically, Mosaic contains data from the HES database (coarse health bands; cancers and others; and long term conditions); General Health Census data; a number of general health categories from the British Household Panel Survey (BHPS); and Sport England survey data.

However, whilst health data is used in the Mosaic citizen classification system it must be recognised that it would be a misuse of the geodemographic database to analyse the predicted health of a household or postcode explicitly in comparative assessment with air quality (Gilmore, 2011). This is because the data typifies the Mosaic group or type and does not infer information of the individual household explicitly. This is recognised as a limitation in the dataset as discussed in Section 2.10. Instead health and other data comparisons should be limited to inter type or group comparison. Whilst it would be possible to compare household air quality data to a variety of HES health data sources of real relevance to a health and air quality study including, for example, *acute and chronic upper and lower respiratory infection*, this methodology fails to consider the outputs in the context of customer profiling. Thereby, following discussion with NHS health professionals, this line of study was not pursued directly (Gilmore, 2011). Furthermore, as it was not possible to obtain micro-scale health data in the context of this research, this micro-scale study does not directly look at the relationship between health and air quality, or health and deprivation. Nonetheless, comments are made on the predicted health of the Mosaic groups and types relative to other Mosaic classification following the findings of the EJ assessment.

### 5.2.2 **Micro-scale versus Meso-scale Comparison analysis**

Prior to the completion of a micro-scale EJ assessment in Durham it was necessary to review the performance of the air quality modelling. The comparison was completed in two phases. Firstly, a review of comparative AIRE emissions estimates was completed to review the emissions outputs compared to the meso-scale study based on NAEI average speed based emission factors. This analysis was performed prior to expanding the micro-scale model to cover a full 24 hour day, as a sense check to ensure the methodology yielded results broadly comparable to those from the more established method. Therefore, for the AIRE based modelling only results for the AM and PM peaks are presented (07:00-09:30; and 15:00-18:30). Secondly, after the emissions were dispersed, the resultant model output performance was reviewed relative to both monitored air quality data, and modelled outputs from the meso-scale study. Clearly, this more in-depth analysis was performed after it was established the IEM based emissions outputs had proved to be within the expected magnitude.

### 5.2.2.1 Comparative Emissions Results

Analysis was performed to investigate the relationship between the NOx Emissions results derived from the traditional NAEI-based methodology and the AIRE derived IEM technique. Each network was split into approximately 30 road sections to aid comparison.

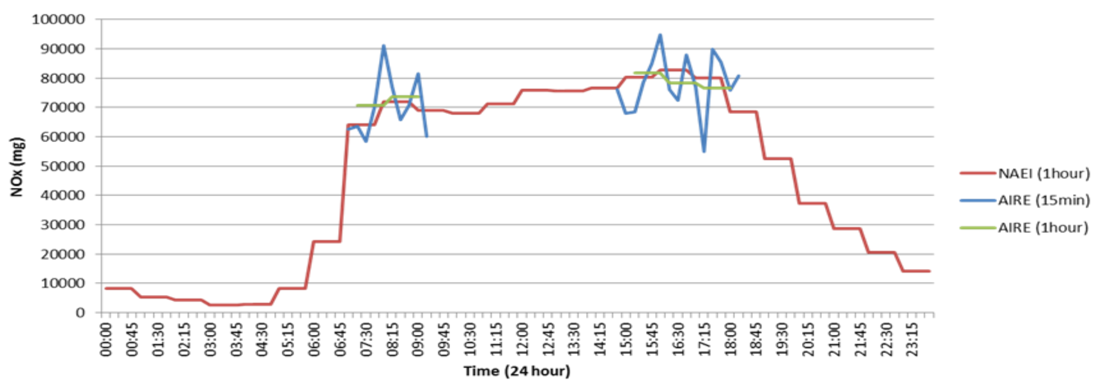



Figure 28. Framwellgate north bound link emissions (NOx).

Figure 28 shows a sample comparison of emission outputs for Framwellgate. Average speed NAEI emissions are presented for a full 24 hour period, at one hour resolution. IEM emissions outputs were aggregated into 15 minute averages, as well as hourly averages to compare directly with the average speed emissions results. A close correspondence between the two methodologies was identified on a number of links providing confidence in the techniques adopted.

However, further analysis of the traffic and related outputs revealed that a large number of links showed evidence of 'congestion' emissions in the AIRE results. Figure 29 shows the modelled shoulders either side of the peak periods which demonstrate good agreement between the two methodologies. Conversely, during the peak, when congestion is highest, significant increases in emissions outputs derived using the AIRE methodology were found. The 15 minute time resolution better indicated when, within the three hour peak period, the congestion 'events' occurred compared to the hourly modelling approach.

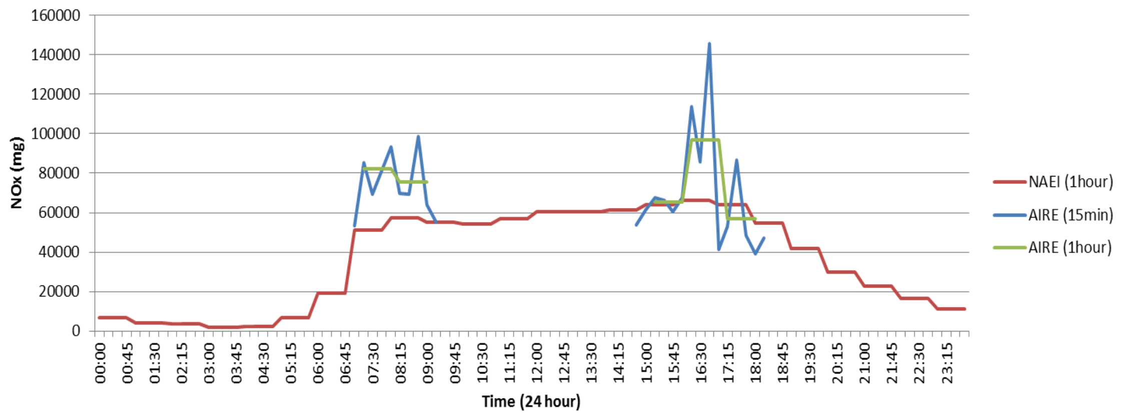



Figure 29. Framwellgate south bound link emissions (NOx).

Furthermore, an analysis of a number of arterial routes provided evidence of tidal congestion emissions. Figure 30 and Figure 31 show the Crossgate Peth area of Durham City. During the morning peak the eastbound movement is congested with people travelling into Durham, with significant increase in emissions in the AIRE outputs compared to the average speed NAEI results. However, in the afternoon peak, when flows going in to Durham are lower, conditions were found to be less congested and the two methods were in better agreement.

Conversely, for the westbound movement it is the afternoon peak when congestion is observed due to high volumes of traffic leaving Durham. Once again the AIRE emissions agreed well with the NAEI-based methodology except in the congested period.

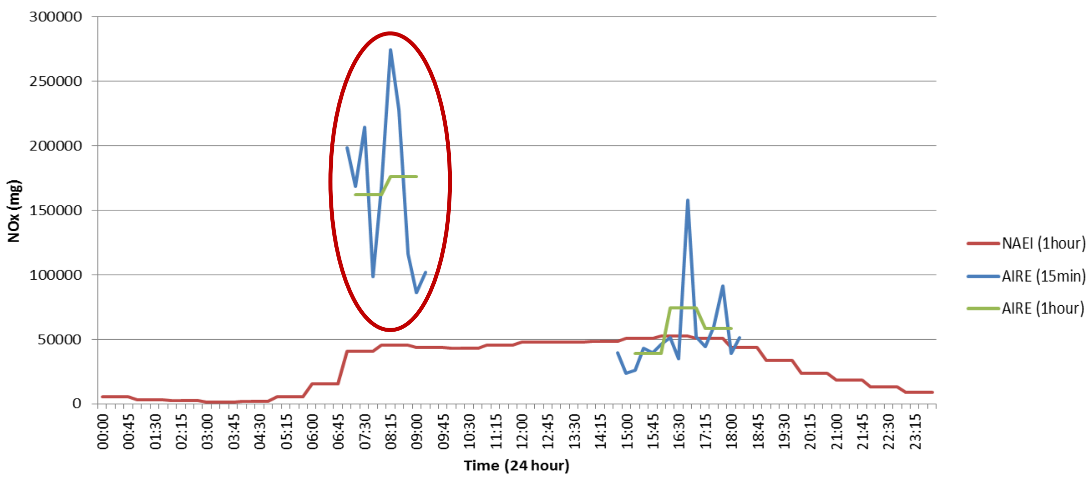



Figure 30. Crossgate Peth east bound link emissions (NOx).

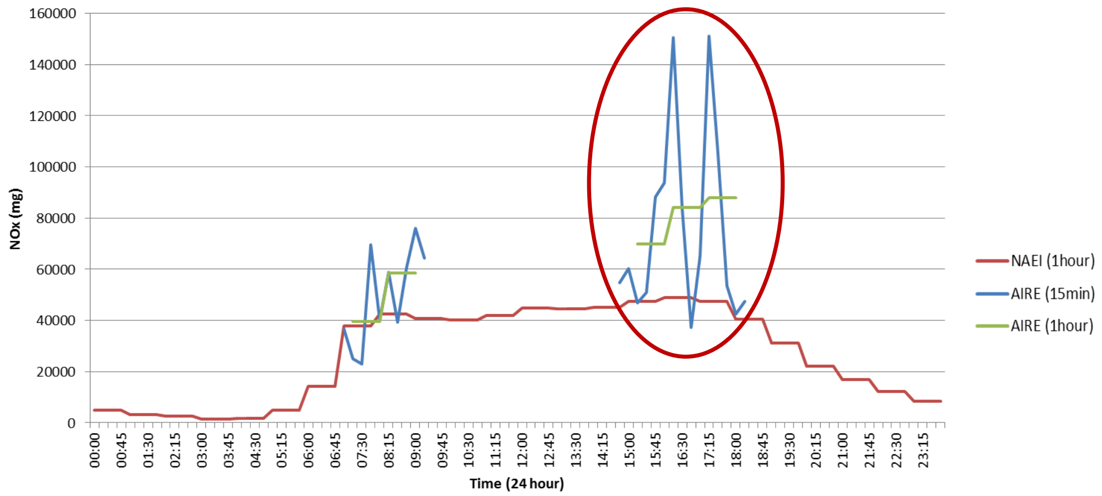



Figure 31. Crossgate Peth west bound link emissions (NOx).

Across the network, significant differences in modelled emissions between the two methodologies were observed. The most heavily congested links revealed +200% higher emissions predicted using AIRE compared to the NAEI outputs. The overall network results can be seen in Table 21.

Table 21 Overall network results, NAEI vs. AIRE (NOx).

| **Peak** | NOx **(mg) NAEI** | NOx **(mg) AIRE** | **Difference (mg)** | **Difference (%)** |
|---|---|---|---|---|
| AM | 10,782,900 | 17,454,206 | 6,671,306 | 62 |
| PM | 19,261,700 | 26,830,555 | 7,568,855 | 39 |

**5.2.2.2** Air Quality Concentrations

Following the emissions based comparison it was evident that the IEM base emissions approach has the potential to provide more accurate air quality modelling. Therefore, the existing micro-simulation model was extended to cover a full 24 hour period, in order to allow the build-up and dispersal of emissions throughout the day to influence concentrations (See discussion in Section 3.3).

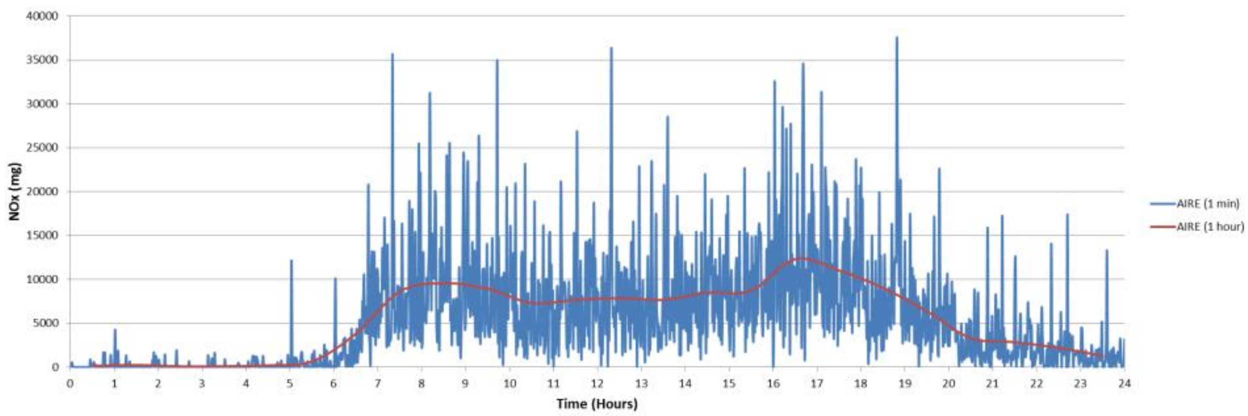



Figure 32. 24 hour emissions output for Framwellgate North (NOx).

Figure 32 shows 24 hour minute by minute emissions output from AIRE for a typical link. The 'minute-by-minute' emissions results were aggregated into hourly values for all links in the network. In this assessment modelled NOx values were converted to $NO_2$ using the DEFRA 'NOx to $NO_2$' calculator version 3.1, published in September 2012 (DEFRA, 2012b). The year and region for which the modelling has been undertaken were specified, and local factors such as an appropriate factor of NOx emitted as $NO_2$, have been used in the calculation. These values were then fed onto a dispersion model enabling comparison of concentrations from the existing network compared to the proposed scheme.

In order to assess the relative success of the IEM derived dispersion model outputs, and those from the NAEI derived modelling, both outputs have been compared to observed data at sixteen monitor sites maintained by DCC (Table 22).

Table 22 Annual mean concentration $NO_2$ concentrations.

| | | Annual mean concentration $NO_2$ ($\mu gm^{-3}$) | | | | |
|---|---|---|---|---|---|---|
| **ID** | **Location** | **Observed** | **AIRE** | **NAEI** | **FB $_{(AIRE)}$** | **FB $_{(NAEI)}$** |
| 1 | Milburngate | 34.5 | 27.88 | 25.90 | 0.21 | 0.28 |
| 2 | Highgate North | 42.9 | 30.69 | 28.83 | 0.33 | 0.39 |
| 3 | Gilesgate | 43.4 | 29.23 | 28.20 | 0.39 | 0.42 |
| 4 | Claypath | 31.4 | 24.21 | 24.15 | 0.26 | 0.26 |
| 5 | Sherburn Road | 25.2 | 26.9 | 28.42 | -0.07 | -0.12 |
| 6 | Dragon Lane | 41.6 | 37.81 | 24.25 | 0.10 | 0.53 |
| 7 | 121 Gilesgate | 35.1 | 31.14 | 26.88 | 0.12 | 0.27 |
| 8 | The Gates | 43.2 | 39.26 | 29.12 | 0.10 | 0.39 |
| 9 | Claypath | 37.7 | 32.21 | 25.46 | 0.16 | 0.39 |
| 10 | Young Street | 27.4 | 24.96 | 27.21 | 0.09 | 0.01 |
| 11 | 56 McKintosh court | 18.4 | 19.06 | 19.84 | -0.04 | -0.08 |
| 12 | 56 McKintosh court | 19.7 | 20.92 | 23.38 | -0.06 | -0.17 |
| 13 | 49 Sunderland Road | 18.3 | 20.25 | 21.60 | -0.10 | -0.17 |
| 14 | The Sands | 17.7 | 18.56 | 18.28 | -0.05 | -0.03 |
| 15 | Monitor Gilesgate 1 | 22.2 | 27.26 | 26.25 | -0.20 | -0.17 |
| 16 | Monitor Gilesgate 2 | 21.8 | 27.26 | 26.25 | -0.22 | -0.19 |

Figure 33 shows a scatter plot of observed versus predicted annual mean concentration $NO_2$ $\mu gm^{-3}$ for both modelling approaches.

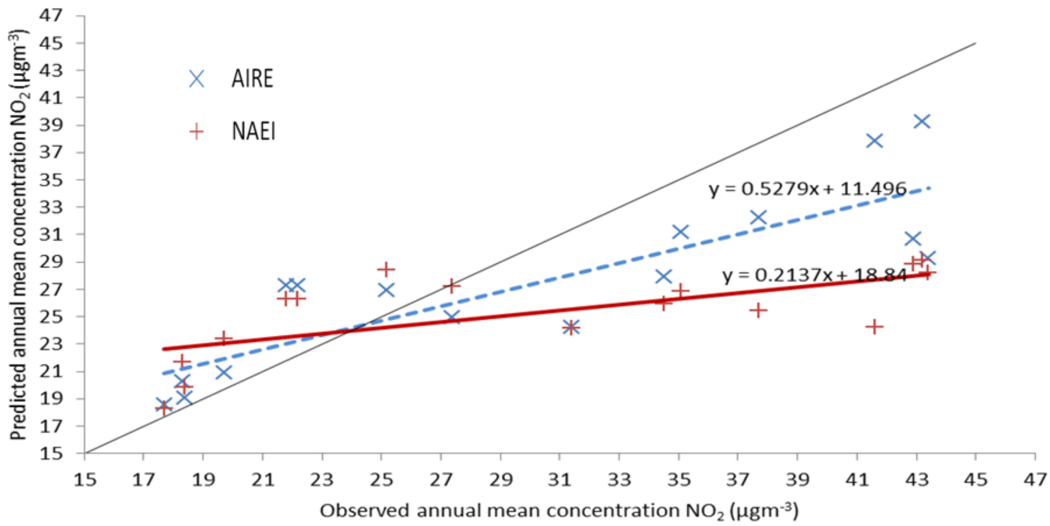



Figure 33. Observed versus predicted annual mean concentration $NO_2$ $\mu gm^{-3}$.

Linear regression shows that the AIRE linked with ADMS model produces an $R^2$ value of 0.72, compared with 0.43 for the NAEI-ADMS model. This suggests a good association between the variables for both models, particularly in the AIRE-ADMS model. Though linear regression revealed the gradient of both lines to be different from 1, an analysis of fractional bias (FB) using the methodology of Chang and Hanna (2005) did not produce evidence of a systematic under- or over- prediction in either model. FB is a measure of mean bias. It is documented in the literature as being a robust evaluation performance measure (Chang and Hanna, 2005). It indicates the mean under or over-prediction (Hanna et al., 2004). FB ranges from -2 (over-prediction) to +2 (under-prediction) and a perfect model has an FB of zero (Hanna et al., 2004). For both models FB values were within a factor of two ($-2/3 > FB < 2/3$) of the observed, indicating no systematic under or over-prediction for either model. Furthermore, FB values were closer to zero for the AIRE-ADMS model at 12 of the 16 monitor sites. Moreover, a review of site specific results for both models shows that the AIRE-ADMS model more accurately predicted $NO_2$ concentrations at 12 of the 16 sites when compared to the NAEI-ADMS model. Additionally, at eight of the sites this enhanced accuracy was a result of a higher concentration prediction for the AIRE-ADMS model when compared to the NAEI-ADMS model. Many of these sites were located in central areas of Durham including Milburngate, Highgate North, The Gates, and Gilesgate, where congestion and delay is highest. This can be considered evidence that the AIRE-ADMS approach allowed for better capture of 'congestion' emissions, highlighting the benefit of this approach to air quality modelling.

This analysis has shown that the use of an IEM (AIRE) to derive emissions for use in a dispersion model (ADMS) more accurately reflects observed data, compared to the more traditional approach using average speed-based factors. It is suggested that this enhanced accuracy comes from the ability of this approach to more accurately capture 'congestion' emissions in critical locations. Therefore, this modelling approach was adopted for the micro-scale EJ study presented in the following section.

### 5.2.3 **Micro-scale Environmental Justice Results**

The meso-scale EJ study presented in Chapter 4 indicated that there was no evidence of environmental injustice in the distribution of air quality in the City of Durham. This study provides an opportunity to review those findings at the micro-scale level. The study was conducted in accordance with the methodology outlined in the previous sections.

Analysis of Mosaic and air quality data revealed that, in agreement with the meso-scale study, there was no evidence of any significant relationship between air quality and deprivation. This was confirmed by analysis of Mosaic deprivation score and predicted $NO_2$ at each of the 7471 households ($R^2 = 0.002$) (Figure 34).

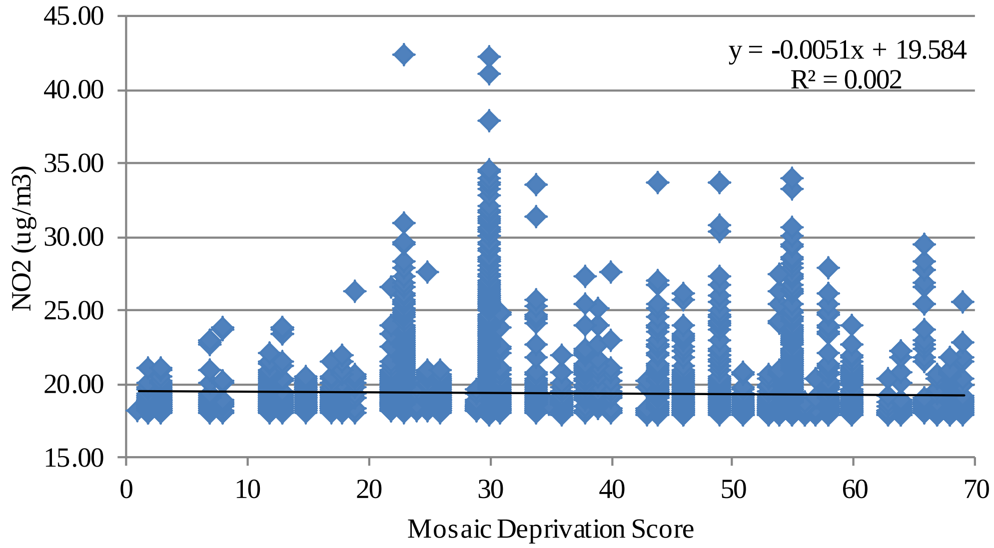



Figure 34. Mosaic Deprivation Score and $NO_2$ for Durham households.

Similarly, when analysing the data by group there was no linear relationship between the Mosaic deprivation score of a group and its mean air quality concentration ($NO_2$) (Figure 35). For example, the most deprived Mosaic group, Group O, had a mean $NO_2$ concentration of 18.43µgm$^{-3}$ compared to the highest mean $NO_2$ concentration of 20.57µgm$^{-3}$ for Group G.

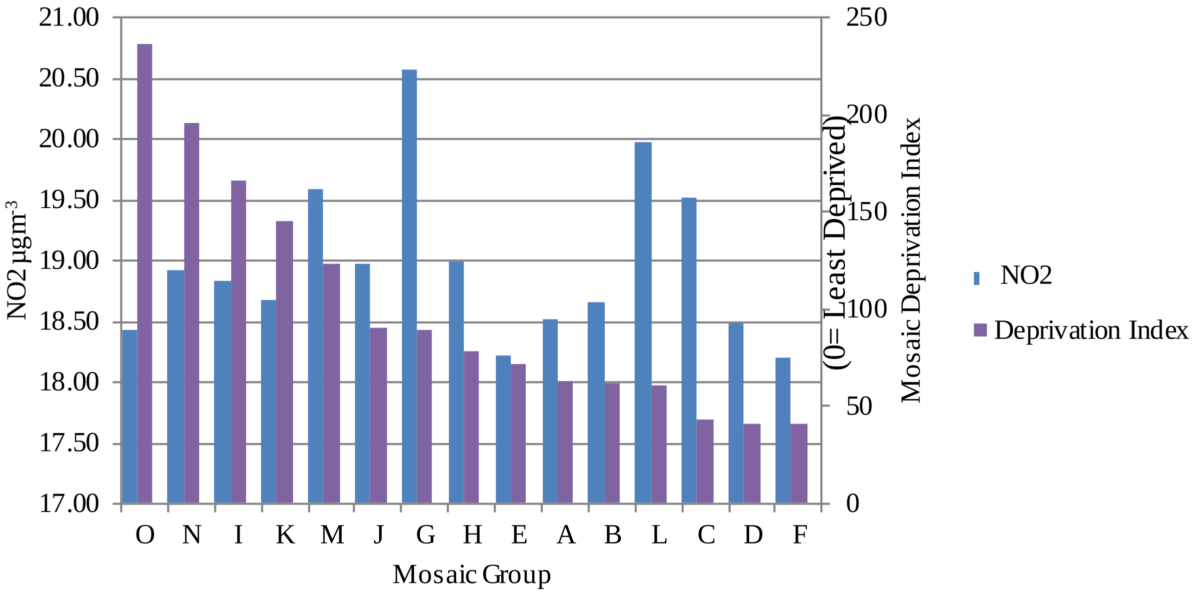



Figure 35. Mosaic deprivation Index and Mean $NO_2$.

However, further analysis of group and type data revealed significant features in the groups subjected to poor air quality. Households were classed as being exposed to air quality ($NO_2$) 'above 25 µgm$^{-3}$' or '25 µgm$^{-3}$ and below'. 25 µgm$^{-3}$ was chosen to divide the total household population for two reasons. Firstly, the background $NO_2$ in Durham is typically 17 µgm$^{-3}$ (See Section 4.2.5) and 25 µgm$^{-3}$ represents a value where air quality is being influenced by local pollution but falls well below the 40 µgm$^{-3}$ EU limit; secondly, this value allowed for a sufficiently large cohort of households in the 'poorer' air quality group. The geo-demographic groups were themselves allocated into one of three groups; group C, *Wealthy people living in sought after neighbourhoods*; group G, *Young, well-educated city dwellers'*; and *Other* (which refers to all those not in the previously defined groups). These groups were based on the numbers falling into the 'above 25 µgm$^{-3}$' category and each group was individually tested for significant variance.

Chi squared analysis was performed to determine if the magnitude of discrepancy between the observed and expected data was significant. Namely, were the groups that make up the population living in Durham's poorest air quality areas over represented when compared to the expected representation of those groups, given their prominence in the UK population, based on nationwide Mosaic data.

Overall, chi squared analysis showed statistically significant differences at the 95% confidence level between the expected and observed values indicating significant over-representation compared to the expected population of both group C and group G in the 'above 25 µgm$^{-3}$' category (Figure 36). Therefore, these results show that higher counts of both the identified groups are present in Durham's poorest air quality areas than could be expected given their prominence in the UK population as a whole.

Group G account for 9% of UK population and 30% of the Durham study area population (2209 of 7471 households). However, 73% of study area households with air quality above 25 µgm$^{-3}$ (151 of 208 households) and 100% of study area households with air quality above 35 µgm$^{-3}$ (40 households) where classified as Group G. Therefore, the only households subject to air pollution levels above the mandatory EU air quality limit value for $NO_2$ of 40 µgm$^{-3}$ belonged to this group.

| | | | Group | | Total |
|---|---|---|---|---|---|
| | | | G | Other | |
| Concentration | 25 or Below | Count | 2059 | 5205 | 7264 |
| | | Expected Count | 2147.8 | 5116.2 | 7264.0 |
| | Above 25 | Count | 150 | 57 | 207 |
| | | Expected Count | 61.2 | 145.8 | 207.0 |
| Total | | Count | 2209 | 5262 | 7471 |
| | | Expected Count | 2209.0 | 5262.0 | 7471.0 |

| | Value | df | Asymp. Sig. (2-sided) | Exact Sig. (2-sided) | Exact Sig. (1-sided) |
|---|---|---|---|---|---|
| Pearson Chi-Square | 188.113 | 1 | .000 | | |
| Continuity Correction[b] | 186.001 | 1 | .000 | | |
| Likelihood Ratio | 167.113 | 1 | .000 | | |
| Fisher's Exact Test | | | | .000 | .000 |
| N of Valid Cases | 7471 | | | | |

$\chi^2 = 188.113$, df = 1, p = 3.841 at 0.05 probability level

Figure 36. Chi Squared result for Group G.

| | | | Concentration | | |
|---|---|---|---|---|---|
| | | | 25 or Below | Above 25 | Total |
| Group | C | Count | 685 | 30 | 715 |
| | | Expected Count | 695.2 | 19.8 | 715.0 |
| | Other | Count | 6579 | 177 | 6756 |
| | | Expected Count | 6568.8 | 187.2 | 6756.0 |
| Total | | Count | 7264 | 207 | 7471 |
| | | Expected Count | 7264.0 | 207.0 | 7471.0 |

| | Value | df | Asymp. Sig. (2-sided) | Exact Sig. (2-sided) | Exact Sig. (1-sided) |
|---|---|---|---|---|---|
| Pearson Chi-Square | 5.961 | 1 | .015 | | |
| Continuity Correction[b] | 5.390 | 1 | .020 | | |
| Likelihood Ratio | 5.251 | 1 | .022 | | |
| Fisher's Exact Test | | | | .022 | .013 |
| N of Valid Cases | 7471 | | | | |

$\chi^2 = 5.961$, df = 1, p = 3.841 at 0.05 probability level

Figure 37. Chi Squared result for Group C.

| | | | Concentration | | Total |
|---|---|---|---|---|---|
| | | | 25 or Below | Above 25 | |
| Group | C | Count | 685 | 30 | 715 |
| | | Expected Count | 695.2 | 19.8 | 715.0 |
| | G | Count | 2059 | 150 | 2209 |
| | | Expected Count | 2147.8 | 61.2 | 2209.0 |
| | Other | Count | 4520 | 27 | 4547 |
| | | Expected Count | 4421.0 | 126.0 | 4547.0 |
| Total | | Count | 7264 | 207 | 7471 |
| | | Expected Count | 7264.0 | 207.0 | 7471.0 |

| | Value | df | Asymp. Sig. (2-sided) |
|---|---|---|---|
| Pearson Chi-Square | 217.870 | 2 | .000 |
| Likelihood Ratio | 216.716 | 2 | .000 |
| N of Valid Cases | 7471 | | |

$\chi^2 = 217.870$, df = 2, p = 5.991 at 0.05 probability level

Figure 38. Overall Chi Squared result for Group C and G

Neither Group G, nor Group C could be regarded as deprived social groups (Experian, 2009). In terms of deprivation they are ranked 7 and 13 out of the 15 groups respectively (with 1 being the most deprived group) (Experian, 2009). Mosaic 'imagery' is presented in Figure 39. Therefore, these findings are contrary to the perceived established relationship between air quality and socio-economic status identified in a number of UK EJ studies.


Figure 39. Imagery from Mosaic Public Sector, Group G left, and C right.

Furthermore, analysis of Mosaic type data shows that only two types within Group G were over-represented in their exposure to poor air quality. Type 32 *'Students and other transient singles in multi-let houses'* account for 18% of the Durham study area population (1344 of 7471 households); yet represent 45% of study area households with air quality above 25 $\mu gm^{-3}$ (93 of 208 households) and 75% above 35 $\mu gm^{-3}$. Similarly, Type 34 *'Students involved in college and university communities'* account for 18% of Durham study area population (1344 of 7471 households); but represent 24% of study area households with air quality above 25 $\mu gm^{-3}$ (49 of 208 households) and 25% above 35 $\mu gm^{-3}$. Whilst the existence of this relationship is likely to be due to the historic nature of Durham and the location of Durham University, it is nonetheless an important finding and consideration should be given to this when deciding on improvement options for air quality in Durham.

As described in Section 2.10, whilst health data is used in the Mosaic classification, due to the typified nature of the data, Mosaic parameters do not explicitly infer a direct household level result. Therefore, it was not deemed appropriate to perform a detailed comparative assessment comparing the predicted health of a household and its predicted air quality concentration (Gilmore, 2011). (See Section 5.2.1). However, comments on the specific health of the Mosaic groups and types are provided. Specifically, a review of the predicted health of the significantly over-represented groups in the 'above 25 $\mu gm^{-3}$' category is presented (Group G, and C), along with predicted health information for the identified types identified in the EJ analysis (Type 32 and 34).

Firstly, the Mosaic 'General Health' parameter was selected in the Mosaic database to provide an overview of the health of the over-represented groups. Group G, was ranked 6/15 for 'General Health', with 1 being the healthiest, indicating it as a comparably healthy group. Group C, was ranked 1/15 identifying it as being the healthiest overall group.

Table 23 shows the Mosaic index scores, mean percentage of Groups C and G, and Types 32 and 34 for a variety of health parameters identified in Section 2.3 (See also **Appendix A**) as having an association with air pollution. For comparative purposes the mean percentage score for the UK population across all groups is also provided, along with the group and type ranking for the individual health parameters. It was not possible to directly match relevant HES codes recommended by COMEAP (2013) due to limitations in the Mosaic dataset. Health parameters reported on include respiratory associated illnesses including asthma; and cardiovascular related illness (COMEAP, 2010; COMEAP, 2013; COMEAP, 2015). COMEAP provides independent advice to the government on the impact of air pollution on health. Guidance from COMEAP is supported by a large body of research with its members encompassing a range of specialist fields such as air quality science, atmospheric chemistry, toxicology, physiology, epidemiology, statistics, paediatrics and cardiology. Directly relevant research includes Atkinson et al (2014) which provides evidence of links between chronic asthma and air pollution; Atkinson et al (2001) which reports on the effects of air pollution on respiratory admissions; Checkoway et al (2000) who produced analysis of the impact of air pollution on cardiovascular illness; and Hedley et al (2002) who explore air pollutions impact on cardiorespiratory and all-cause mortality.

Index scores are calculated by dividing the mean group percentage by the mean percentage across all groups, times 100. All results provided refer to averages across the UK, and are not region specific. Whilst analysis of regional variation in health parameters may influence the results, it was not possible to complete this analysis due to limitations in the Mosaic licensing available for this research.

Table 23 Mosaic Health Data (Group C and G) – Relevant to Durham study area population.

| Group / Type | Health Parameter | Index | Mean (%) | Mean (all groups / types) (%) | Rank (1 = highest) |
|---|---|---|---|---|---|
| C | Acute upper respiratory infections | 50 | 0.12 | 0.24 | 14/15 |
| | Chronic lower respiratory diseases | 35 | 0.20 | 0.57 | 15/15 |
| | Lung diseases due to external agents | 112 | 0.05 | 0.04 | 4/15 |
| | Other acute lower respiratory infections | 65 | 0.20 | 0.31 | 14/15 |
| | Other diseases of upper respiratory tract | 74 | 0.14 | 0.19 | 15/15 |
| | Other forms of heart disease | 87 | 0.59 | 0.68 | 8/15 |
| | Pulmonary heart disease | 72 | 0.06 | 0.08 | 12/15 |
| | Cancers of resp/ intrathoracic organs | 51 | 0.12 | 0.24 | 13/15 |
| | J45-46 Asthma | 49 | 0.08 | 0.16 | 15/15 |
| G | Acute upper respiratory infections | 66 | 0.16 | 0.24 | 11/15 |
| | Chronic lower respiratory diseases | 57 | 0.32 | 0.57 | 12/15 |
| | Lung diseases due to external agents | 75 | 0.03 | 0.04 | 12/15 |
| | Other acute lower respiratory infections | 61 | 0.18 | 0.31 | 15/15 |
| | Other diseases of upper respiratory tract | 87 | 0.16 | 0.19 | 12/15 |
| | Other forms of heart disease | 58 | 0.39 | 0.68 | 13/15 |
| | Pulmonary heart disease | 63 | 0.06 | 0.08 | 13/15 |
| | Cancers of resp/ intrathoracic organs | 54 | 0.13 | 0.24 | 12/15 |
| | J45-46 Asthma | 79 | 0.13 | 0.16 | 9/15 |

| | | | | | |
|---|---|---|---|---|---|
| G32 | Acute upper respiratory infections | 86 | 0.21 | 0.24 | 34/69 |
| | Chronic lower respiratory diseases | 57 | 0.37 | 0.57 | 55/69 |
| | Lung diseases due to external agents | 79 | 0.04 | 0.04 | 48/69 |
| | Other acute lower respiratory infections | 70 | 0.21 | 0.31 | 59/69 |
| | Other diseases of upper respiratory tract | 85 | 0.16 | 0.19 | 53/69 |
| | Other forms of heart disease | 57 | 0.39 | 0.68 | 58/69 |
| | Pulmonary heart disease | 65 | 0.06 | 0.08 | 54/69 |
| | Cancers of resp/ intrathoracic organs | 58 | 0.14 | 0.24 | 52/69 |
| | J45-46 Asthma | 88 | 0.15 | 0.16 | 37/69 |
| G34 | Acute upper respiratory infections | 50 | 0.12 | 0.24 | 57/69 |
| | Chronic lower respiratory diseases | 21 | 0.12 | 0.57 | 69/69 |
| | Lung diseases due to external agents | 18 | 0.01 | 0.04 | 68/69 |
| | Other acute lower respiratory infections | 25 | 0.08 | 0.31 | 69/69 |
| | Other diseases of upper respiratory tract | 45 | 0.09 | 0.19 | 69/69 |
| | Other forms of heart disease | 19 | 0.13 | 0.68 | 68/69 |
| | Pulmonary heart disease | 19 | 0.02 | 0.08 | 68/69 |
| | Cancers of resp/ intrathoracic organs | 11 | 0.03 | 0.24 | 69/69 |
| | J45-46 Asthma | 41 | 0.07 | 0.16 | 67/69 |

A number of interesting findings can be attained from a review of Table 23. It is evident that both Group C and Group G are relatively healthy groups when considering health parameters associated with air pollution. The Mosaic 'index' scores are less than 100 for all health parameters with the exception of "Lung diseases due to external agents" (Index = 112) discussed below. This indicates that these groups and types are underrepresented when measured against the UK population as a whole.

Group C's lowest ranking relevant health parameter is *"Lung diseases due to external agents"* (Ranked 4/15). Significantly, the mean percentage of Group C citizens suffering from *"Lung diseases due to external agents"* (0.05), is higher than the national average across all groups (0.04). This is a surprising result given the relative health of the group across the majority of reviewed parameters. Whilst it fits logically with the results of this research, given that in Durham Group C is identified as being over represented in poor air quality areas, it was anticipated that this finding was unique to Durham; and this explanation is not valid for Group C across the UK. The result is discussed further in the EJ assessment of Newcastle and Gateshead.

However, with the exception of the aforementioned health parameter, Group C recorded a lower mean percentage of respondents for all the other considered health parameters when compared to the UK population at large. Similarly, Group G's lowest ranking parameter is *"J45-46 Asthma"* (9/15). However, Group G citizens are still 0.03% less likely to suffer from this illness when compared to the national average. Furthermore, both Group C and Group G are actually identified as the healthiest overall groups for some relevant health parameters with a known association with air pollution (e.g. Group C: *Chronic lower respiratory diseases; J45-46 Asthma*; and Group G: *Other acute lower respiratory infections*) (See Section 2.3; **Appendix A**).

Table 23 also reveals that the two Mosaic types identified as being overexposed to Durham's poorest air quality are also relatively healthy when considering relevant health parameters. Type G34 is identified as the overall healthiest type for 4 of the 9 health parameters most relevant to air pollution available in the Mosaic database. For example, when considering *Chronic lower respiratory diseases,* 0.12% of Type G34 citizens are identified as suffering this ailment, compared to 0.57% of the UK total population. The lowest ranking score, for *"Acute upper respiratory infections"* (57/69) still records a mean percentage value half that of the national average. Whilst, Type G32 does not rank as highly across the majority of health parameters, the mean percentage of respondents for both types is lower than that of the UK population for all the considered parameters.

Whilst this data is not intended to contribute to the understanding of the relationship between health and air quality, it is nonetheless of direct relevance to EJ. It is encouraging to note that the distribution of air pollution in Durham, whilst unjust, does not act to inversely impact any vulnerable groups or types. This is in contrast to the findings in Gateshead, discussed in Section 5.3. It is suggested that this information should be considered by engineers and planners tackling air quality issues so they may be aware of the EJ implications of the distribution of air pollution across their cities.

### 5.2.4 **Summary**

When considering health, the results from the Durham study reflect the extremely complex relationship between health; and the potential impact of air quality (Walker, 2012). The type of analysis performed in this research provides further evidence of the need for epidemiology studies when investigating links between air quality and health (Namdeo and Stringer, 2008).

## 5.3 Newcastle upon Tyne and Gateshead Environmental Justice Study

### 5.3.1 **Study Areas**

As discussed in Chapter 1 and Section 3.4, three case study North East cities have been considered in this research. In addition to the Durham investigations, EJ assessments of Newcastle and Gateshead have been conducted and findings compared and contrasted to allow more definitive findings and greater assurance that the established modelling framework can be applied across different locations and scales.

Newcastle and Gateshead were selected as suitable study areas for two key reasons. Firstly, the author had previous involvement with Newcastle/Gateshead Low-Emission Zone Feasibility Study: Vehicle Emissions and Air Quality Modelling (Goodman et al.,, 2013), which ensured familiarity with the area and that air quality modelling was readily available. Secondly, both Newcastle and Gateshead have significant air quality issues and both councils are actively monitoring and reviewing air quality levels, ensuring data availability. As a result of identified air quality issues, historically AQMAs have been declared by both Newcastle City Council and Gateshead Council.

In Newcastle: the City Centre, Quayside, adjacent to the A1058 Jesmond Road/Cradlewell, Blue House Roundabout, and parts of the A189 and B1318 Gosforth High Street (Goodman et al.,, 2013). More recently, the three former, and the two latter AQMA boundaries have been altered to form two larger AQMAs, both declared for exceedance of the Nitrogen Dioxide annual mean standard. Within this study, the two areas are referred to as the Newcastle City Centre and Gosforth AQMAs. Gateshead has currently declared two AQMAs, Gateshead Town Centre and an area adjacent to services on the A1M at Birtley. As with Newcastle, the Gateshead AQMAs were declared for exceedance of the Nitrogen Dioxide annual mean standard. Within this study the two areas are referred to as the Gateshead and Birtley AQMAs (Goodman et al., 2013).

The location of the AQMAs within the Tyne and Wear region is shown in Figure 40.

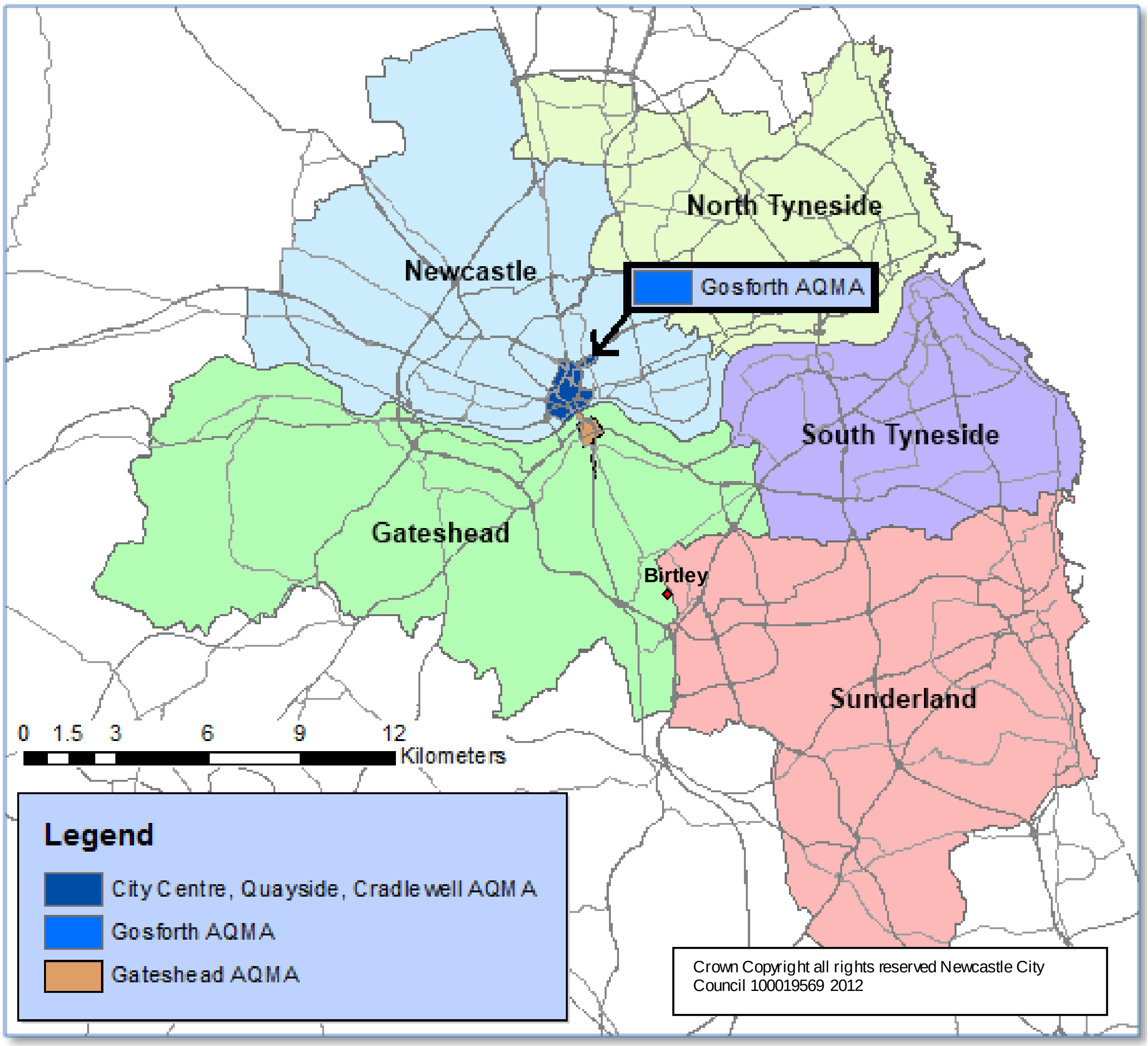



Figure 40. Location of Declared Newcastle and Gateshead Air Quality Management Areas (AQMAs) within Tyne and Wear Region. Major motorways, A-roads and B-roads are also shown (Adapted from Goodman et al., 2013).

The study areas selected for inclusion in the EJ assessment follow the postcode boundary for Newcastle and Gateshead (Figure 41). Following consultation with Newcastle and Gateshead councils, it was decided that despite their geographical proximity the EJ assessment of the two cities should be completed individually. This was due to the significant contrast between the socio-economic make-up of the two cities; and the disaggregated approach the cities have to tackling air quality issues (Section 5.3.3).

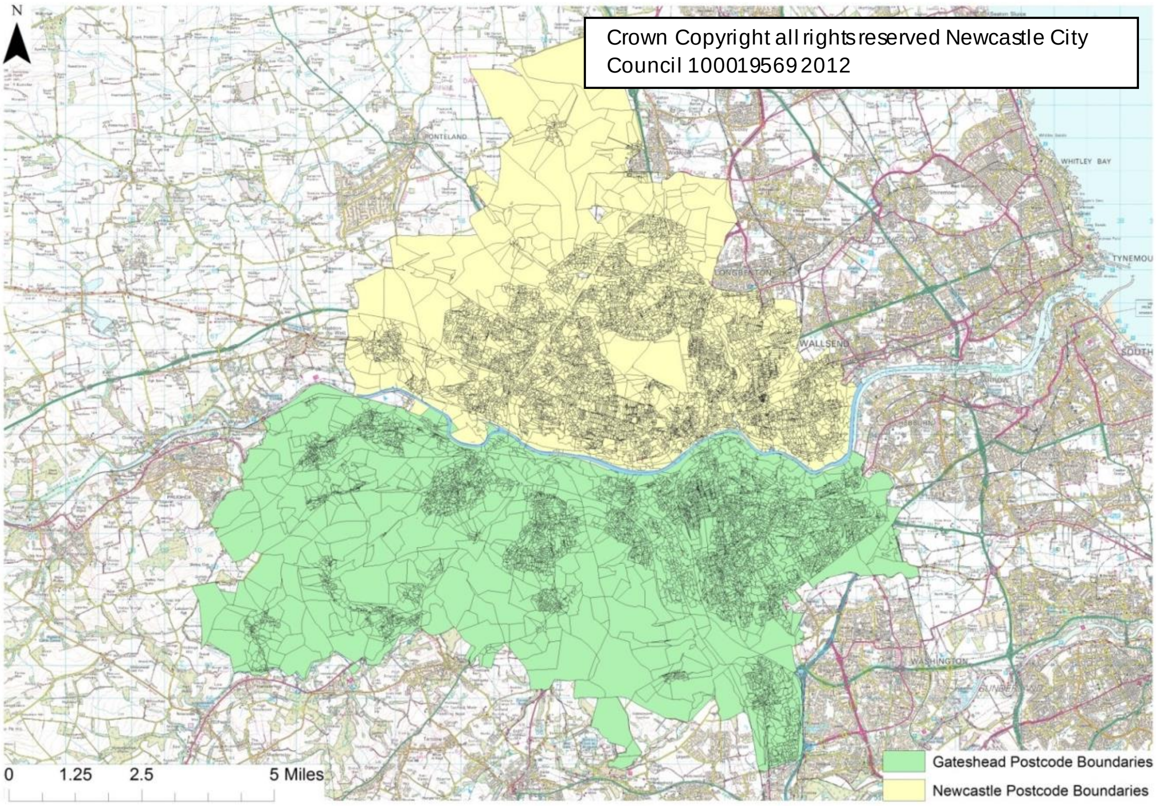



Figure 41. Newcastle and Gateshead postcode boundaries and study area.

### 5.3.2 **Methodology Summary**

As with the Durham meso-scale and micro-scale studies described in Chapter 4 and Section 5.2 respectively, the modelling framework outlined in Chapter 3 was revisited and revised to ensure its suitability for investigating EJ in both Newcastle and Gateshead. The modelling structure presented in Chapter 3, Figure 3 has been expanded below to provide details of the modelling and data packages adopted for the Newcastle and Gateshead study. The models, processes and structures behind each stage of framework are discussed in detail in Chapter 3.

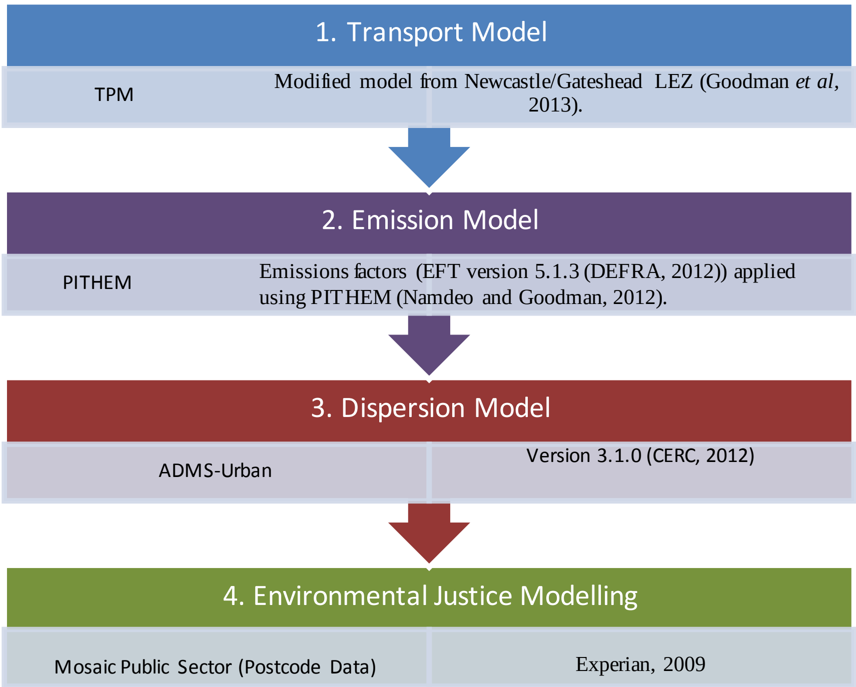



Figure 42. Newcastle and Gateshead Modelling Methodology

Three fundamental variations in methodology should be noted when considering the results of the EJ assessment in Newcastle and Gateshead. Firstly, the increased size of the study areas meant the micro-scale modelling approach, adopted during the micro-scale Durham study for obtaining emissions and subsequent air quality concentration values was not appropriate (Section 2.9). Therefore, in line with the meso-scale Durham pilot study, strategic level traffic modelling was used to provide necessary transport data. Furthermore, strategic level traffic modelling necessitated a suitable emissions calculation methodology. Thereby, PITHEM was used to calculate emissions from road transport in line with the pilot study presented in Chapter 4. Finally, when considering Environmental Justice Modelling it was necessary to address the limitations identified in the pilot study of using LSOA scale geodemographic data. Finer resolution data was sought to enable a more comprehensive EJ assessment of the spatial distribution of air quality. Whilst household level data was not available to the author, postcode level data from the Public Sector Mosaic database was obtained (Experian, 2009) (See Section 2.10). In total 5841 and 4846 postcode areas were considered in Newcastle and Gateshead respectively. Finally, the EJ assessment was completed by comparing $NO_2$ outputs and Mosaic data, for all postcode areas across the two cities, using the analytical methods applied in the Durham study (Section 5.2.3).

### 5.3.3 Environmental Justice Results

As with the previous studies described in this research, air quality and Mosaic data were analysed to determine if there was any significant linear relationship between air quality and deprivation in both Newcastle and Gateshead. Mosaic deprivation scores and predicted $NO_2$ for all postcodes were plotted to explore the relationship between the variables (Newcastle: $R^2 = 0.037$; Gateshead: $R^2 = 0.017$) (Figure 43 and Figure 44).

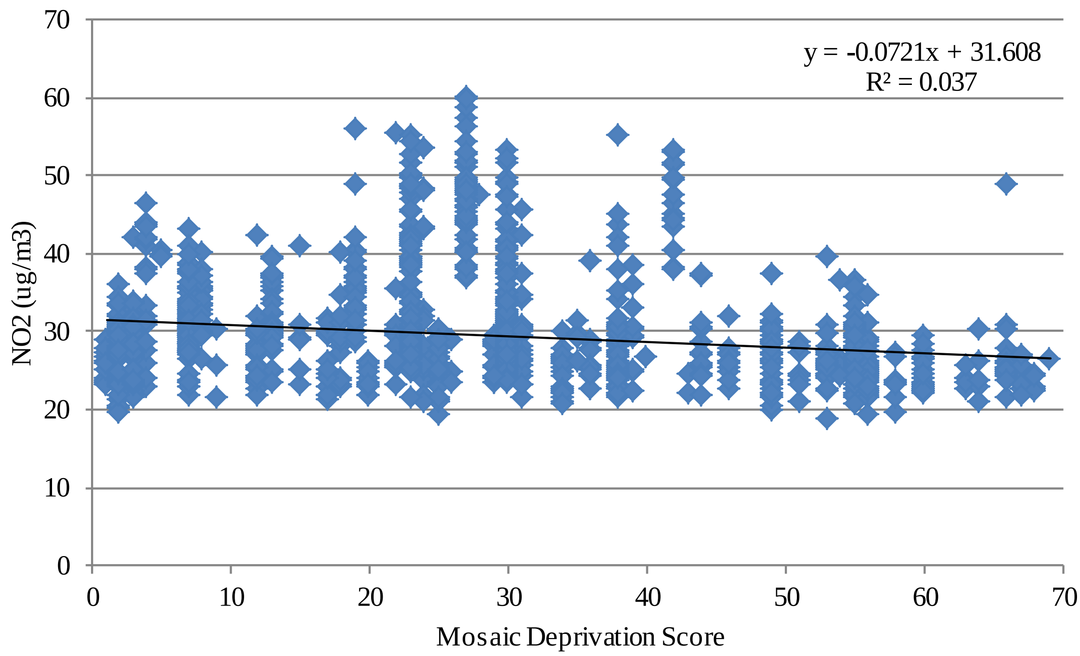



Figure 43. Mosaic Deprivation Score and $NO_2$ for Newcastle postcodes

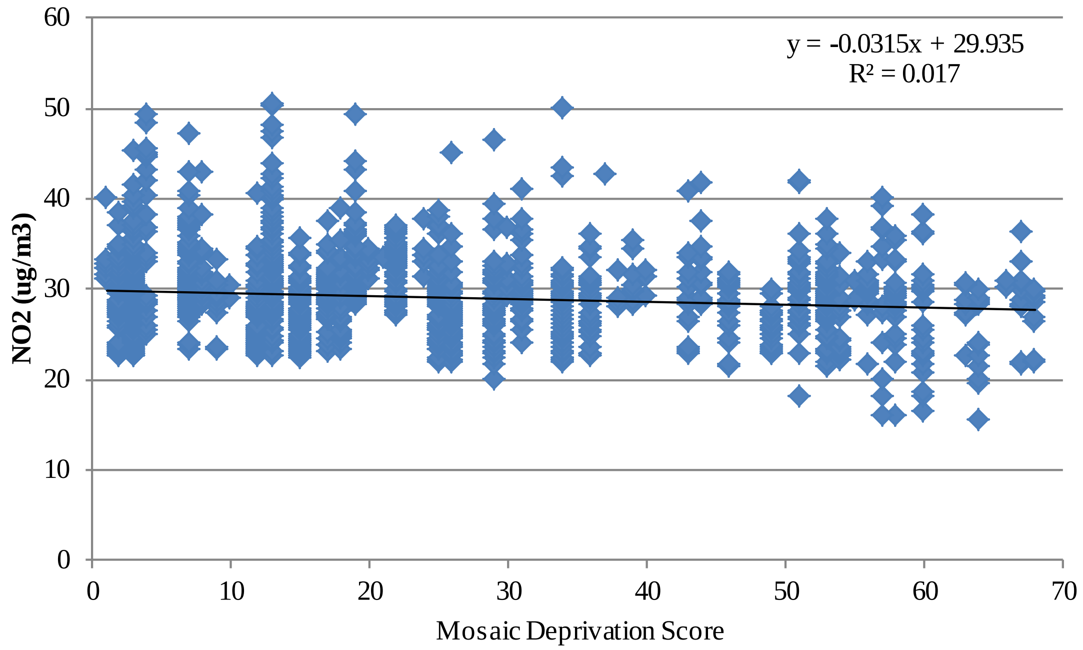



Figure 44. Mosaic Deprivation Score and $NO_2$ for Gateshead postcodes

The regression analysis revealed that, as in Durham, there is no evidence of a significant linear relationship between air quality and deprivation. Nonetheless, further analysis of group and type data was completed following the procedure set out in the Durham study (Section 5.2.3). Once again, through the application of chi squared analysis significant features were discovered in the types and groups subjected to poor air quality.

In the Durham study, households were classed as being exposed to air quality ($NO_2$) 'above 25 µgm$^{-3}$' or '25 µgm$^{-3}$ and below' (Section 5.2.3). The 25 µgm$^{-3}$ level was selected to disseminate the total household population in Durham as it represented a value where air quality is being influenced by local pollution but fell below the 40 µgm$^{-3}$ EU limit; and the value allowed for a sufficiently large cohort of households in the 'poorer' air quality group (Section 5.2.3).

The dissemination level was reviewed for its suitability in Newcastle and Gateshead. Firstly, background levels of $NO_2$ were reviewed for the two cities. For the Newcastle and Gateshead modelling, background pollutant levels and non-transport sources were taken directly from the latest DEFRA source-apportioned background maps (DEFRA, 2016). Annual mean values for 2010 were 18.2 and 16.8 µgm$^{-3}$ (NOx as $NO_2$) for Newcastle and Gateshead respectively. These values are considered broadly in line with the background concentration in Durham. However, when reviewing the modelled air quality concentrations across the two cities, it was found that there was a far greater sample of higher $NO_2$ concentrations than in the Durham study. For example, in Durham the 'above 25 $\mu gm^{-3}$' group accounted for 208 households out of a sample of 7471. However, in Newcastle and Gateshead, over half the considered postcode areas fell in to the 'above 25 $\mu gm^{-3}$ category. As this study is focused on reviewing the geodemographics of the poorest air quality areas for the respective cities it was decided to set the segregation level at 'above 35 $\mu gm^{-3}$. This level ensured that in Newcastle, 287 of 2481 postcode areas would be classed in the poorer air quality group; and in Gateshead 153 of 1743 fell in to the same group. It is noted that the segregation levels are set below the 40 $\mu gm^{-3}$ EU limit value for $NO_2$. However, in the context of EJ the value considered is of little consequence, given that in this instance $NO_2$ is effectively being used as a proxy for poor air quality, due to its relevance in the study areas; and that more recent air quality research suggests that there are no safe limits for some pollutants (COMEAP, 2013; Buonanno et al., 2017).

Following the procedure set out in the Durham study, the geo-demographic groups were then reviewed and allocated into appropriate groups based on the numbers falling into the poorer air quality category. Firstly, considering Newcastle, it was evident that it was most appropriate to apportion the population into two groups, group G, *Young, well-educated city dwellers'*; and *Other* (which refers to all other groups). Individually, group G accounted for 69% of study area postcodes with air quality above 35 $\mu gm^{-3}$ (197 of 287 postcode areas). No other group accounted for more than 6% of study area postcodes with air quality above 35 $\mu gm^{-3}$.

The groups were tested for significant variance. Chi squared analysis showed statistically significant differences at the 95% confidence level between the expected and observed values indicating significant over representation compared to the expected population of group G in the 'above 35 $\mu gm^{-3}$' category (Figure 45). Furthermore, Group G accounts for 9% of UK population and 31% of the Newcastle study area population (774 of 2481 postcode areas). However, 69% of study area households with air quality above 35 $\mu gm^{-3}$ (197 of 287 postcode areas) and 84% of study area households with air quality above 40 $\mu gm^{-3}$ (the mandatory EU air quality limit value for $NO_2$) were classified as Group G.

| | | | Concentration Group | | |
|---|---|---|---|---|---|
| | | | 0 | 35 | Total |
| Group | G | Count | 197 | 577 | 774 |
| | | Expected Count | 89.5 | 684.5 | 774.0 |
| | Other | Count | 90 | 1617 | 1707 |
| | | Expected Count | 197.5 | 1509.5 | 1707.0 |
| Total | | Count | 287 | 2194 | 2481 |
| | | Expected Count | 287.0 | 2194.0 | 2481.0 |

| | Value | df | Asymp. Sig. (2-sided) | Exact Sig. (2-sided) | Exact Sig. (1-sided) |
|---|---|---|---|---|---|
| Pearson Chi-Square | 211.990[a] | 1 | .000 | | |
| Continuity Correction[b] | 210.022 | 1 | .000 | | |
| Likelihood Ratio | 194.568 | 1 | .000 | | |
| Fisher's Exact Test | | | | .000 | .000 |
| N of Valid Cases | 2481 | | | | |

$\chi^2 = 211.990$, df = 1, p = 3.841 at 0.05 probability level

Figure 45. Chi Squared result for Newcastle

Following the chi squared analysis of Newcastle; the procedure was repeated for the Gateshead study area. A review of the data in the poorer air quality category revealed it was most appropriate to apportion the population into four groups: group G, '*Young, well-educated city dwellers'*; group N, *'Young people renting flats in high density social housing'*; group M, *'Elderly people reliant on state support'*; and *Other* (which refers to all other groups).

Individually, group G, N and M accounted for 12%, 22% and 20% of study area postcodes with air quality above 35 μgm$^{-3}$ respectively (18, 33 and 31 of 153 postcode areas). No other individual group accounted for more than 7% of study area postcodes with air quality above 35 μgm$^{-3}$. The identified groups were tested for significant variance. Overall, chi squared analysis showed statistically significant differences at the 95% confidence level between the expected and observed values indicating significant over representation compared to the expected population of groups N, M and G in the 'above 35 μgm$^{-3}$' category (Figure 46; Figure 47; and Figure 48 respectively).

| | | | ConcentrationGroup | | Total |
|---|---|---|---|---|---|
| | | | .00 | 35.00 | |
| Group | N | Count | 33 | 150 | 183 |
| | | Expected Count | 16.1 | 166.9 | 183.0 |
| | Other | Count | 120 | 1440 | 1560 |
| | | Expected Count | 136.9 | 1423.1 | 1560.0 |
| Total | | Count | 153 | 1590 | 1743 |
| | | Expected Count | 153.0 | 1590.0 | 1743.0 |

| | Value | df | Asymp. Sig. (2-sided) | Exact Sig. (2-sided) | Exact Sig. (1-sided) |
|---|---|---|---|---|---|
| Pearson Chi-Square | 21.871[a] | 1 | .000 | | |
| Continuity Correction[b] | 20.599 | 1 | .000 | | |
| Likelihood Ratio | 17.811 | 1 | .000 | | |
| Fisher's Exact Test | | | | .000 | .000 |
| N of Valid Cases | 1743 | | | | |

$\chi^2 = 21.871$, df = 1, p = 3.841 at 0.05 probability level

Figure 46. Chi Squared result for Group N in Gateshead.

| | | ConcentrationGroup | | Total |
|---|---|---|---|---|
| | | .00 | 35.00 | |
| Group M | Count | 31 | 187 | 218 |
| | Expected Count | 19.1 | 198.9 | 218.0 |
| Group Other | Count | 122 | 1403 | 1525 |
| | Expected Count | 133.9 | 1391.1 | 1525.0 |
| Total | Count | 153 | 1590 | 1743 |
| | Expected Count | 153.0 | 1590.0 | 1743.0 |

| | Value | df | Asymp. Sig. (2-sided) | Exact Sig. (2-sided) | Exact Sig. (1-sided) |
|---|---|---|---|---|---|
| Pearson Chi-Square | 9.216[a] | 1 | .002 | | |
| Continuity Correction[b] | 8.456 | 1 | .004 | | |
| Likelihood Ratio | 8.089 | 1 | .004 | | |
| Fisher's Exact Test | | | | .004 | .003 |
| N of Valid Cases | 1743 | | | | |

$\chi^2 = 9.216$, df = 1, p = 3.841 at 0.05 probability level

Figure 47. Chi Squared result for Group M in Gateshead.

| | | | ConcentrationGroup | | Total |
|---|---|---|---|---|---|
| | | | .00 | 35.00 | |
| Group | G | Count | 18 | 53 | 71 |
| | | Expected Count | 6.2 | 64.8 | 71.0 |
| | Other | Count | 135 | 1537 | 1672 |
| | | Expected Count | 146.8 | 1525.2 | 1672.0 |
| Total | | Count | 153 | 1590 | 1743 |
| | | Expected Count | 153.0 | 1590.0 | 1743.0 |

| | Value | df | Asymp. Sig. (2-sided) | Exact Sig. (2-sided) | Exact Sig. (1-sided) |
|---|---|---|---|---|---|
| Pearson Chi-Square | 25.391[a] | 1 | .000 | | |
| Continuity Correction[b] | 23.280 | 1 | .000 | | |
| Likelihood Ratio | 17.988 | 1 | .000 | | |
| Fisher's Exact Test | | | | .000 | .000 |
| N of Valid Cases | 1743 | | | | |

$\chi^2 = 25.391$, df = 1, p = 3.841 at 0.05 probability level

Figure 48. Chi Squared result for Group G in Gateshead.

| | | ConcentrationGroup | | Total |
|---|---|---|---|---|
| | | .00 | 35.00 | |
| Group | G | Count | 18 | 53 | 71 |
| | | Expected Count | 6.2 | 64.8 | 71.0 |
| | M | Count | 31 | 187 | 218 |
| | | Expected Count | 19.1 | 198.9 | 218.0 |
| | N | Count | 33 | 150 | 183 |
| | | Expected Count | 16.1 | 166.9 | 183.0 |
| | Other | Count | 71 | 1200 | 1271 |
| | | Expected Count | 111.6 | 1159.4 | 1271.0 |
| Total | | Count | 153 | 1590 | 1743 |
| | | Expected Count | 153.0 | 1590.0 | 1743.0 |

| | Value | df | Asymp. Sig. (2-sided) |
|---|---|---|---|
| Pearson Chi-Square | 68.166[a] | 3 | .000 |
| Likelihood Ratio | 57.617 | 3 | .000 |
| N of Valid Cases | 1743 | | |

Figure 49. Overall Chi Squared results for Gateshead

A further interesting observation from the Mosaic data review was the relative lack of Group G citizens in Gateshead when compared to the national levels, and those for

Durham and Newcastle. Group G accounts for 9% of UK population, 32% and 31% of the Durham and Newcastle study area populations. Conversely, only 4% of the Gateshead study area population are classed as group G (71 of 1743 postcode areas). This result is likely to reflect the fact that Gateshead does not have a university, reducing its student population. Nonetheless, 12% of study area postcodes with air quality above 35 $\mu gm^{-3}$ where classified as Group G providing further evidence of injustice for this group across all study areas despite the relatively small population size in this instance.

Conversely, whilst Group N accounts for 5.5% of UK population, 10.5% of Gateshead's postcodes are allocated to this group. Furthermore, 21.6% of study area postcodes with air quality above 35 $\mu gm^{-3}$ were classified as Group N. Again, this provides evidence behind the statistically significant over-representation of Group N identified in the chi squared analysis. Finally, Group M accounts for 5.3% of UK population and 12.5% of Gateshead's postcodes. Whilst 20.3% of the poorer air quality category are represented by this group confirming over-representation of the group in its exposure to Gateshead's poorer air quality.

The statistically significant over-representation of Mosaic groups in Gateshead is in contrast to that identified in Durham and Newcastle. In both Durham and Newcastle the over-represented groups subject to poorer air quality are relatively affluent (Section 5.2.3). Conversely, in Gateshead the most significant over-represented groups are classed as deprived. This identified EJ concern in Gateshead follows the more established pattern regarding the distribution of air quality relative to social deprivation (Mitchell and Dorling, 2003; Mitchell et al, 2015).

Group N and group M are both deprived social groups according to the Experian Mosaic database. Group N is ranked as the second most deprived of the 15 Mosaic groups; Group M is the fifth most deprived (See Experian, 2009). Mosaic 'imagery' is presented in Figure 50. Therefore, these findings suggest the relationship between air quality and socio-economic status identified in a number of UK EJ studies is present in Gateshead (Section 2.5.3).


Figure 50. Imagery from Mosaic Public Sector, Group N left, and M right

In addition to the analysis of Mosaic group data, Mosaic type data was reviewed as part of the EJ assessment. This revealed that in Newcastle, whilst Group G was over-represented as an overall group, only two of the nine types within Group G were subject to unjust exposure to poor air quality. Type 31 '*Owners in smart purpose built flats in prestige locations, many newly built'* accounts for 2% of the Newcastle study area population (62 of 2481 postcode areas), yet represent 22% of postcode areas with air quality above 35 $\mu gm^{-3}$ (62 of 287 postcode areas). Therefore 100% of postcode areas classed as type 31 are found in areas with $NO_2$ concentrations above 35 $\mu gm^{-3}$. Similarly, Type 34 *'Students involved in college and university communities'* account for 7% of Durham study area population (166 of 2481 postcode areas); but represent 17% of postcode areas with air quality above 35 $\mu gm^{-3}$ (50 of 287 postcode areas). This information provides a critical understanding of the people being affected by poor air quality in Newcastle and confirms the EJ concern raised in the Mosaic group level analysis.

Mosaic type data analysis in Gateshead identified similar instances which could be regarded as a concern when considering the EJ of the spatial distribution of Gateshead's air quality. Firstly, within the over-represented Group G, it was identified that a single type within the group, type 32 '*Students and other transient singles in multi-let houses*' was over-represented in its exposure to poorer air quality. This group accounts for 3% of the Gateshead study area population (58 of 1743 postcode areas); yet represent 11% of postcode areas with air quality above 35 $\mu gm^{-3}$ (17 of 153 postcode areas). Additionally, within group M, type 57 *'Old people in flats subsisting on welfare payments'* was over-represented (6% of Gateshead study area population; 17% of postcode areas with air quality above 35 $\mu gm^{-3}$). And within group N, type 66 *'Childless, low income tenants in high rise flats'* was over-represented in its exposure to poorer air quality (2% of Gateshead study area population; 11% of postcode areas with air quality above 35 $\mu gm^{-3}$). These findings show that the people suffering from the poorest air quality in Gateshead belong to relatively narrow and specific socio-demographic groups.

The EJ assessment in Durham presented earlier in this chapter considered the health of Mosaic groups identified as being over-represented in their exposure to poorer air quality. Further to this, the predicted health of over-represented groups in both Newcastle and Gateshead is presented.

Firstly, Group G was identified as being over-represented in poorer air quality areas across both Newcastle and Gateshead. However, this group was previously identified as being subject to an EJ issue in Durham. Therefore the health of group G, and in particular the assessment of health in relation to diseases and illnesses with known associations with air quality, is discussed in detail in Section 5.2.3 and is not repeated in this section. To provide a brief summary, Group G was ranked 6/15 for 'General Health', with 1 being the healthiest, indicating it as a comparably healthy group. Furthermore, the group recorded lower than mean national results for all air quality related health parameters which were available in the Mosaic database.

As no further Mosaic groups were identified as being significantly over-represented in Newcastle's poorer air quality areas, no further health analysis is presented in Newcastle. Conversely, in Gateshead, as previously discussed, two further Mosaic groups were identified as having disproportionately high exposure to the poorest air quality areas (Group N and M). Therefore, the health parameters of these groups are analysed to complete the EJ assessment of the spatial distribution of Gateshead's air quality, in accordance with the methodology outlined in Chapter 3.

Firstly, the Mosaic 'General Health' parameter was selected in the Mosaic database to provide an overview of the health of the identified over-represented groups. Group N, was ranked 14/15 for 'General Health', with 1 being the healthiest, indicating it as a comparably unhealthy group. Furthermore, Group M was ranked 15/15 identifying it as being the least healthy overall group.

Table 24 shows the Mosaic index scores, mean percentage of groups N and M, and Types 31, 57, and 66 for a variety of health parameters identified in Section 2.3 as having an association with air pollution. This data in conjunction with data from Table 23, which contains data on group G and types 32 and 34 (i.e. Groups and types also subject to exposure to poor air quality in Durham), ensures data for all over-represented Mosaic groups across the two study areas is provided. For comparative purposes the mean percentage score for the UK population across all groups is also provided, along with the group and type ranking for the individual health parameters. As discussed in the Durham study, it was not possible to directly match relevant HES codes recommended by COMEAP (2013) due to limitations in the Mosaic dataset.

Table 24 Mosaic Health Data (Groups N and M and Types G31, M57 and N66) – Relevant to Gateshead and Newcastle study area population.

| Group / Type | Health Parameter | Index | Mean (%) | Mean (all groups / types) (%) | Rank (1 = highest) |
|---|---|---|---|---|---|
| Groups relevant to Gateshead study area population | | | | | |
| N | Acute upper respiratory infections | 119 | 0.30 | 0.24 | 6/15 |
| | Chronic lower respiratory diseases | 137 | 0.78 | 0.57 | 5/15 |
| | Lung diseases due to external agents | 101 | 0.05 | 0.04 | 6/15 |
| | Other acute lower respiratory infections | 109 | 0.33 | 0.31 | 6/15 |
| | Other diseases of upper respiratory tract | 122 | 0.23 | 0.19 | 2/15 |
| | Other forms of heart disease | 79 | 0.53 | 0.68 | 11/15 |
| | Pulmonary heart disease | 90 | 0.08 | 0.08 | 9/15 |
| | Cancers of resp/ intrathoracic organs | 103 | 0.24 | 0.24 | 7/15 |
| | J45-46 Asthma | 153 | 0.25 | 0.16 | 3/15 |
| M | Acute upper respiratory infections | 123 | 0.15 | 0.24 | 5/15 |

| | | | | | |
|---|---|---|---|---|---|
| | Chronic lower respiratory diseases | 385 | 2.20 | 0.57 | 1/15 |
| | Lung diseases due to external agents | 281 | 0.13 | 0.04 | 1/15 |
| | Other acute lower respiratory infections | 244 | 0.73 | 0.31 | 1/15 |
| | Other diseases of upper respiratory tract | 90 | 0.17 | 0.19 | 11/15 |
| | Other forms of heart disease | 297 | 2.12 | 0.68 | 1/15 |
| | Pulmonary heart disease | 237 | 0.21 | 0.08 | 1/15 |
| | Cancers of resp/ intrathoracic organs | 278 | 0.65 | 0.24 | 1/15 |
| | J45-46 Asthma | 123 | 0.20 | 0.16 | 5/15 |
| Types relevant to Newcastle study area population | | | | | |
| G31 | Acute upper respiratory infections | 53 | 0.13 | 0.24 | 56/59 |
| | Chronic lower respiratory diseases | 46 | 0.26 | 0.57 | 58/69 |
| | Lung diseases due to external agents | 52 | 0.02 | 0.04 | 60/69 |
| | Other acute lower respiratory infections | 46 | 0.13 | 0.31 | 66/69 |
| | Other diseases of upper respiratory tract | 88 | 0.17 | 0.19 | 48/69 |
| | Other forms of heart disease | 39 | 0.26 | 0.68 | 64/69 |
| | Pulmonary heart disease | 49 | 0.04 | 0.08 | 63/69 |
| | Cancers of resp/ intrathoracic organs | 45 | 0.11 | 0.24 | 60/69 |
| | J45-46 Asthma | 59 | 0.10 | 0.16 | 56/69 |
| Types relevant to Gateshead study area population | | | | | |
| M57 | Acute upper respiratory infections | 83 | 0.21 | 0.24 | 37/69 |
| | Chronic lower respiratory diseases | 402 | 2.29 | 0.57 | 2/69 |
| | Lung diseases due to external agents | 256 | 0.11 | 0.04 | 5/69 |
| | Other acute lower respiratory infections | 210 | 0.63 | 0.31 | 3/69 |

| | | | | | |
|---|---|---|---|---|---|
| | Other diseases of upper respiratory tract | 115 | 0.22 | 0.19 | 15/69 |
| | Other forms of heart disease | 212 | 1.44 | 0.68 | 5/69 |
| | Pulmonary heart disease | 203 | 0.18 | 0.08 | 5/69 |
| | Cancers of resp/ intrathoracic organs | 305 | 0.72 | 0.24 | 2/69 |
| | J45-46 Asthma | 150 | 0.25 | 0.16 | 10/69 |
| N66 | Acute upper respiratory infections | 116 | 0.29 | 0.24 | 16/69 |
| | Chronic lower respiratory diseases | 209 | 1.20 | 0.57 | 6/69 |
| | Lung diseases due to external agents | 97 | 0.04 | 0.04 | 31/69 |
| | Other acute lower respiratory infections | 136 | 0.41 | 0.31 | 13/69 |
| | Other diseases of upper respiratory tract | 131 | 0.25 | 0.19 | 4/69 |
| | Other forms of heart disease | 118 | 0.80 | 0.68 | 17/69 |
| | Pulmonary heart disease | 136 | 0.12 | 0.08 | 13/69 |
| | Cancers of resp/ intrathoracic organs | 165 | 0.39 | 0.24 | 10/69 |
| | J45-46 Asthma | 137 | 0.23 | 0.16 | 17/69 |

A number of interesting findings can be attained from a review of health parameter data presented in Table 24. It should be noted that, as in the deprivation discussion for Newcastle and Gateshead, health data analysis for Mosaic groups and types identified as being subject to environmental injustice, which were previously identified and discussed in the Durham study, has not been repeated in this section (See Section 5.2.3 in these instances).

It is evident that, in keeping with the general health scores, Group N and Group M are relatively unhealthy groups when considering health parameters associated with air pollution.

Group N's lowest ranking relevant health parameter is *"Other diseases of upper respiratory tract"* (Ranked 2/15). The mean percentage of Group N citizens suffering from *"Other diseases of upper respiratory tract"* (0.23%), is higher than the national average across all groups (0.19%). Furthermore, Group N has higher than average scores for 6 of the 9 considered parameters when compared to the UK population at large.

The health of Group M is of particular concern when examining diseases with a known association with air pollution. Group M is ranked the least healthy group for 6 of the 9 considered health parameters. Furthermore, Group M has higher than average scores for 7 of the 9 considered parameters when compared to the UK population at large. Group M has a particularly large index score for *"Chronic lower respiratory diseases"* (Index 385). This represents a mean percentage score of 2.20, 1.63% higher than the mean percentage score for the UK population. Across the UK, Group M citizens have the highest incidences of *Chronic lower respiratory diseases; Lung diseases due to external agents; Other acute lower respiratory infections; Other forms of heart disease; Pulmonary heart disease; and Cancers of respiration/ intrathoracic organs.* All these diseases have known associations with air pollution; and in many cases are known to be exacerbated by exposure to air pollution (See Section 2.3; and **Appendix A**). Therefore, it is of considerable concern and perversity that the most vulnerable population group should be over-represented in Gateshead's most polluted areas. This finding provides new emphasis on the importance of solving the air quality problems in Gateshead; and addressing the environmental injustice in the distribution of clear air.

Table 24 also reveals three Mosaic types identified as being overexposed to the poorest air quality. Firstly, G31 relates to a type over-represented in Newcastle's poorest air quality areas. In line with the data on Group G, and other types within the group discussed in Section 5.2.3, type 31 is also relatively healthy when considering health parameters relevant to air pollution. Type G31 ranks lowest for *"Other diseases of upper respiratory tract"* (48/69). However, this still represents a mean percentage value below the national average, ensuring the mean percentages are lower than that of the UK population for all considered parameters.

The remaining Mosaic types, M57 and N66 relate to types identified as being overexposed to the poorest air quality in Gateshead. In line with the group results for M and N respectively, these types record substantially higher results. Both M57 and N66 have above mean UK average percent scores for 8 of the 9 health parameters related to air pollution. M57 is ranked second for "*Cancers of resp/ intrathoracic organs"* with a mean percentage value 0.48% above the UK population at large. Finally, N66 is ranked fourth for *"Other diseases of upper respiratory tract"* with a mean percentage value 0.06% above the UK average.

Further to earlier discussion in this chapter, the nature of Mosaic data, obtained using customer profiling, ensures it is unsuitable for reviewing direct relationships between health and air quality. Therefore, this type of analysis is not intended for, and not suitable for, researching direct links between the research themes. However, the results are nonetheless valid, interesting and provide an important contribution to the understanding of the implications of uneven spatial distributions of air quality across our cities. For example, the identification of an over-representation of Group M in the areas of Gateshead with the lowest air quality is a critical finding with a strong implication for EJ.

Similarly, whilst the EJ concern in Newcastle could be regarded as less critical, due to the higher health scores associated with the group and types which are over-represented in Newcastle's poorest air quality areas, a final consideration is the age profile of the identified groups. For example, group M has the oldest age profile of all Mosaic groups; whilst group G has the youngest age profile (Figure 51).

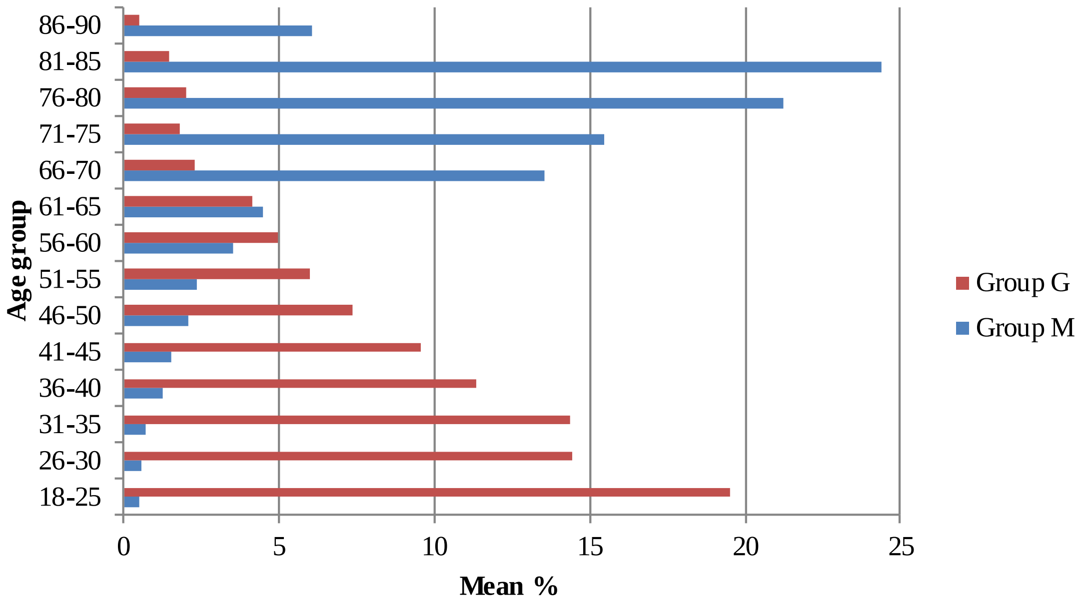



Figure 51. Mean percentage of group respondents falling within age categories for Mosaic Group G and M (Relevant to Newcastle and Gateshead study area population).

Therefore, as there is a relationship between age and many of the considered illness, it is important to consider age when interpreting current health data (See Walker, 2012). Nonetheless, the limitations surrounding causal factors are discussed in Section 2.5.2. Furthermore, the presence of poor air quality amongst areas with higher age groups, who are recognised as being more susceptible to pollutant related illnesses is an EJ concern (Davoudi and Brooks, 2012; Walker, 2012).

### 5.3.4 **Limitations of Approach**

Previous studies, existing literature and findings from this research indicate significant benefits in using IEMs to create emissions outputs, as opposed to using traditional average speed/ average flow derived emissions factors. However, analysis of 24 hour minute by minute emissions outputs has revealed some limitations.

Minute average speed, flow and NOx emissions were plotted for individual links of the modelled network. Typical results can be seen in Figure 52. The graphs show two significant clusters of results broadly defined as ‘free flow’ and ‘congested’ traffic conditions.

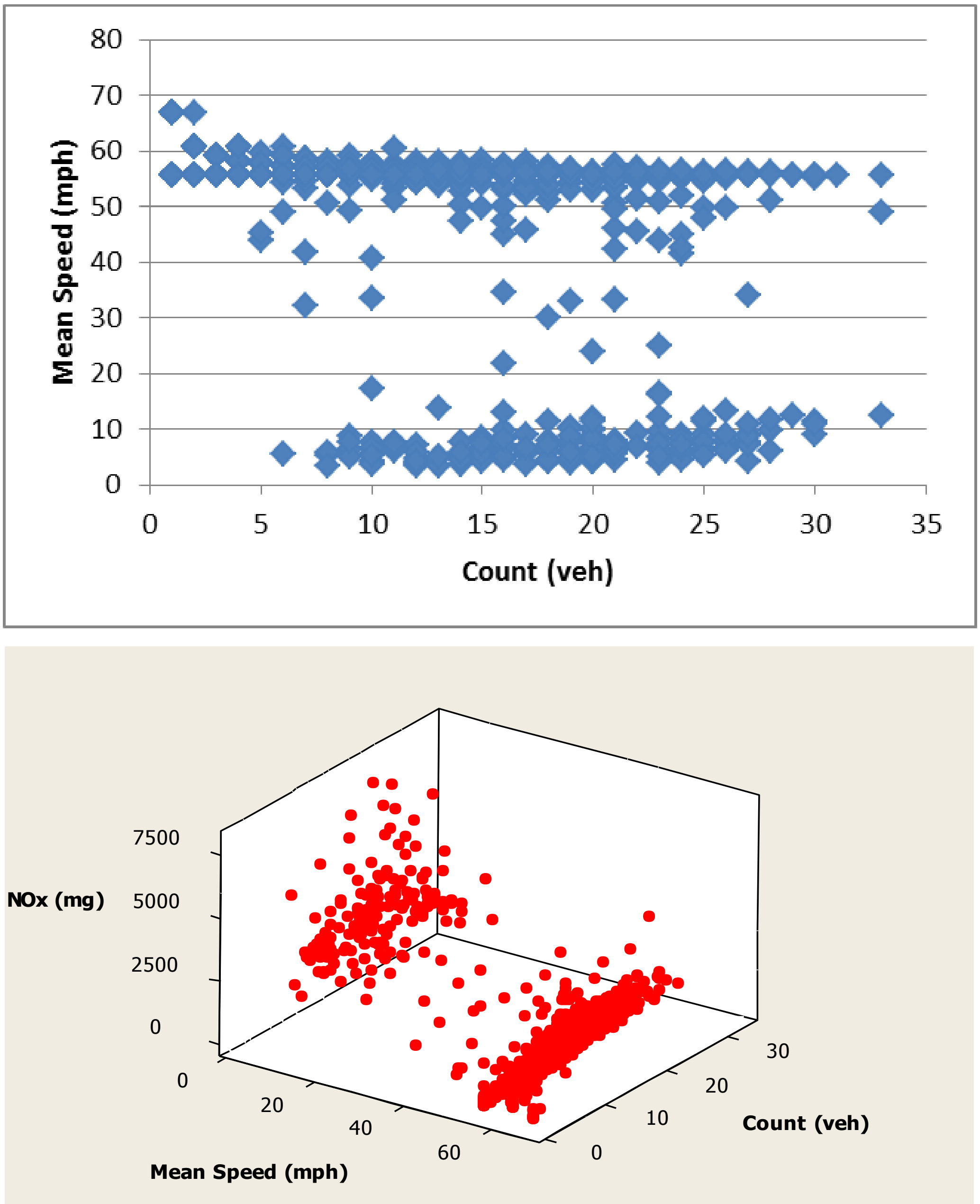



Figure 52. Analysis of minute-by-minute speed, flow and emissions.

Comparing these results to a similar graph from real world Motorway Incident Detection and Automatic Signalling (MIDAS) system data (Figure 52) (Bell et al., 2006), it is evident from analysis of a number of links that the microsimulation may not be correctly simulating the variations in the traffic speeds during the transition phase between traffic states. Whilst it is appreciated not all traffic links will follow the distinct pattern identified in Figure 53, examples of real world emissions analysis following the distinct ‘two state’ pattern identified in the microsimulation have not been found in the literature. It appears that whilst ‘free flow’ and ‘congested’ conditions are accurately represented, the microsimulation model struggles to represent driver behaviour as traffic accelerates/ decelerates in transition to and from congested conditions. As these modes have a first order effect on emissions this is likely to lead to underestimation.

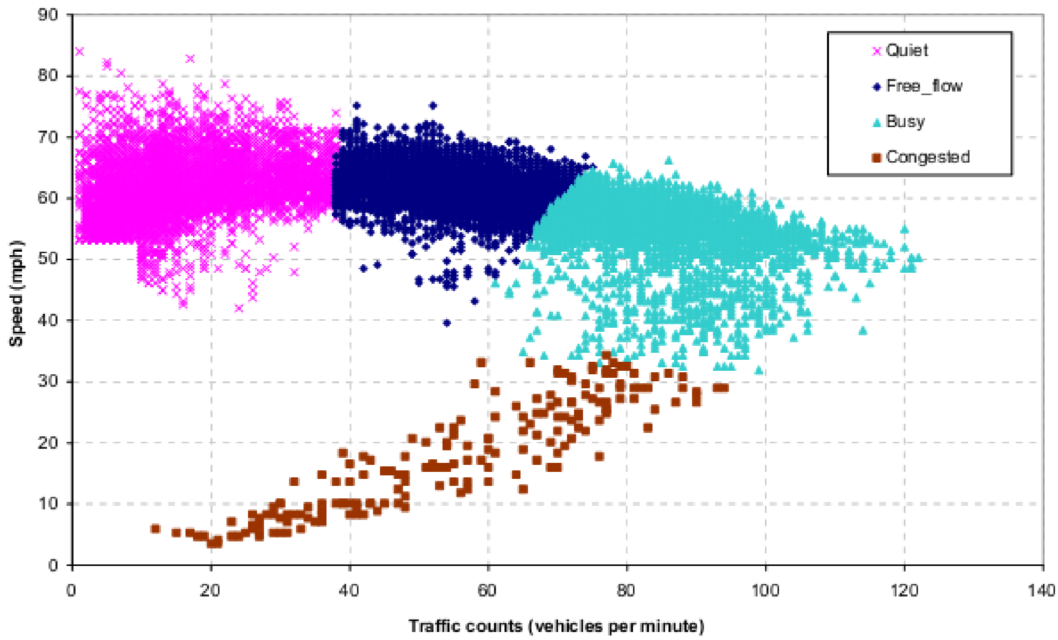



Figure 53. Classification of traffic states on speed flow plot (Bell et al., 2006).

Other limitations include accurate representation of gear changing behaviour which can contribute significantly to overall emissions outputs, and contributes to substantial variation in emissions outputs according to individual driving style (Bell et al., 2006). However, whilst these limitations are acknowledged it is recognised that obtaining direct real world emissions calculations is unlikely to be an achievable goal, particularly in the context of scheme appraisal, and IEMs remain the most accurate way forward for estimating traffic emissions.

### 5.4 Summary

In addition to the Durham investigations, EJ assessments of Newcastle and Gateshead have been conducted and findings compared and contrasted to allow more definitive findings and greater assurance that the established modelling framework can be applied across different locations and scales.

CHAPTER 6

# 6. Impact of Air quality and Carbon management measures on existing EJ concerns

## 6.1 Introduction

Findings from the micro-scale study described in Chapter 5 have revealed that the adopted modelling approach significantly improved the performance of dispersion modelling when measured against monitored data. Furthermore, it was acknowledged that the performance enhancement came due to the ability to more accurately estimate vehicle emissions in congested traffic conditions. The research presented in this chapter aims to exploit this ability by completing a congestion sensitive assessment of traffic management solutions for air quality and low carbon goals that may create only subtle changes in traffic flow regimes.

In this chapter the application of the modelling approach has been tested through investigations into two distinct transport strategies. Firstly, the impact of a traffic engineering scheme aimed at reducing network emissions (specifically $NO_2$) as well as congestion and delay, has been tested. Secondly, reduced VKT strategies have been tested to assess the reduction in traffic required to meet various carbon and air quality targets under varying fleet assumptions.

Additionally, the impact of air quality and carbon management measures on existing EJ concerns have been assessed using the methodology outlined in the 'existing scenario' micro-scale EJ assessment presented in Chapter 5. As in the previous micro-scale study, Durham was selected as an appropriate study area (Chapter 4).

Finally, discussions on the limitations of the modelling approach for the assessment of traffic management solutions, and conclusions from the study are provided.

### 6.2 Durham Traffic Engineering Scheme

As discussed in Section 2.3, in accordance with the Environment Act 1995, DCC were required to produce an AQMA Action Plan (DEFRA, 2010) to address identified air quality issues with the AQMA (Figure 54). Air Quality Action Plans must consider a wide range of emissions reduction strategies and technologies when determining and prioritising Action Plan options. Guidance from DEFRA (LAQM.PG(03) and LAQM.PGA(05)) issued under the Environment Act 1995, provides detailed direction on the preparation and appraisal of Action Plan measures.

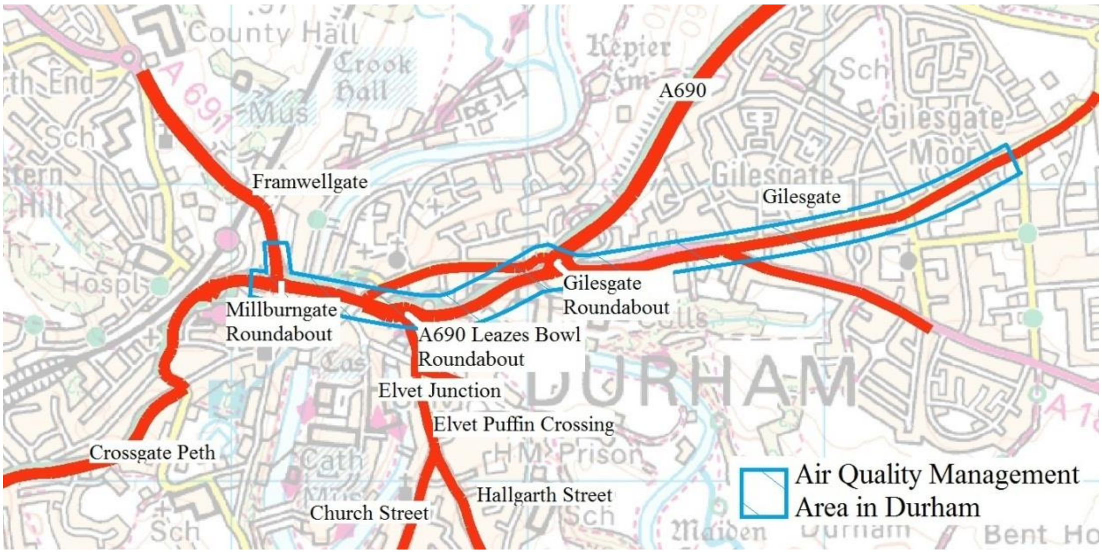



Figure 54. Extent of Air Quality Management Area in Durham.

As transport is the main contributor to poor air quality in 89% of the UK's AQMAs (Chatterton, 2008), understandably, typical Action Plan Options include Public Transport provision; Cycling and Walking Initiatives; Travel Plans; Road User Charging; Demand Management strategies; as well as other non-transport based emission controls (Durham County Council, 2016).

This section presents the results of a comprehensive study of the feasibility of a traffic engineering scheme proposed in Durham. This scheme was developed by DCC traffic team and was under consideration as an Air Quality Action Plan Option during this research. Firstly, the proposed scheme has been described and the methodological approach adopted in the research has been elaborated upon. Next the results are presented in terms of improvement to air quality. Discussion and conclusions follow in subsequent sections.

The stated aims of the scheme are to reduce network emissions (specifically $NO_2$) and reduce congestion and delay. Key features of the scheme include the introduction of traffic signals at two roundabouts (Gilesgate and Leazes Bowl Roundabouts); amending the layout of the Leazes Bowl Roundabout; and co-ordination of the timing of the traffic signals between both the roundabouts and across adjacent junctions.

Key features of the scheme are outlined below:

- Signalising the Gilesgate Roundabout
- Amending and signalising the layout of the Leazes Bowl Roundabout
- Network co-ordination between the roundabouts and across five adjacent junctions and one Puffin crossing.

Initial microsimulation runs of the proposed scheme layout confirmed the importance of co-ordination of traffic signals across the network to prevent queues from one junction interfering with the operation of another upstream.

Co-ordination is possible using the signal controller 'cableless linking facility' (CLF) which operates each junction to rigid timings but has little scope to deal with abnormal traffic conditions or incidents. Alternatively, the Split Cycle Offset Optimisation Technique (SCOOT) could be used to deliver a more dynamic and responsive approach to area control automatically adjusting timings when incidents and events occur in the city that change normal traffic flows and patterns (Chen and Yu, 2007). However, outside of peak traffic periods, e.g. late evening and overnight where flows are at their lowest, SCOOT/CLF is not appropriate because activity in one part of town can lead to unnecessary delays in another part, and without dominant traffic flows, signal co-ordination along routes is not warranted (Chen and Yu, 2007).

With reference to Figure 54 the junctions considered for co-ordination are:

- Church Street / Hallgarth Street Junction ('T' junction with pedestrian facilities)
- Elvet Puffin Crossing
- Elvet Junction ('T' junction with pedestrian facilities)

- A690 Leazes Bowl Roundabout (existing 4 leg roundabout with all four entries within 180°)
- A690 Gilesgate Roundabout (existing 5 leg roundabout) (Figure 55)
- A690/A691 Millburngate Roundabout (4 leg signal controlled roundabout with pedestrian facilities and an entry which includes all buses leaving the bus station) (Figure 56).

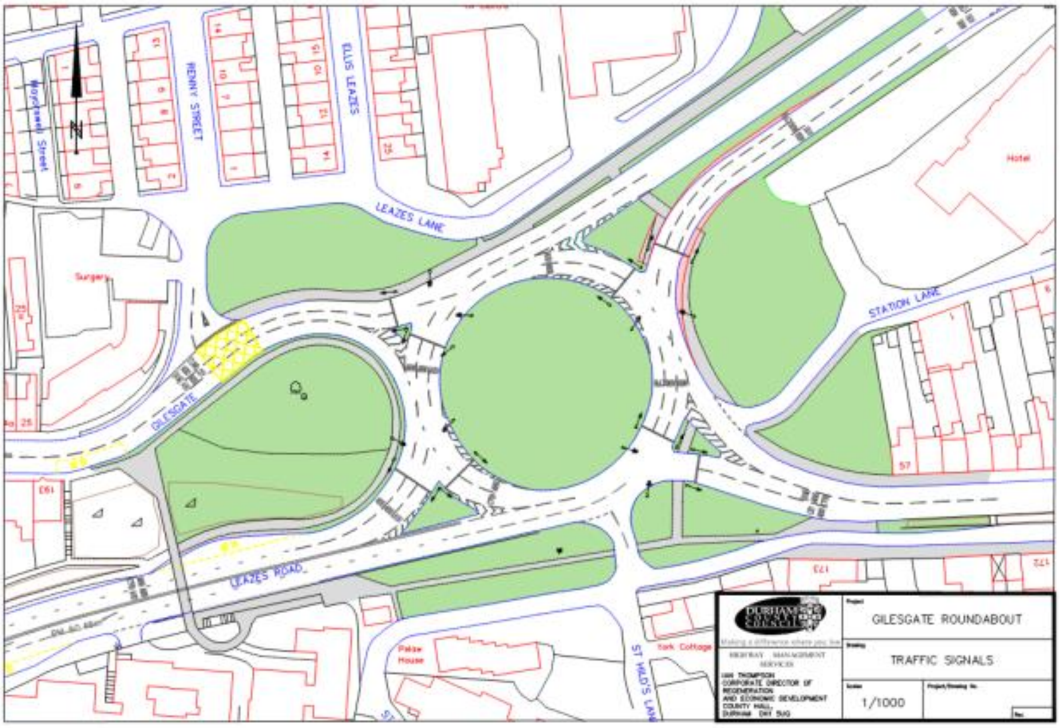



Figure 55. A181 Gilesgate Roundabout – Proposed Traffic Signal Layout.

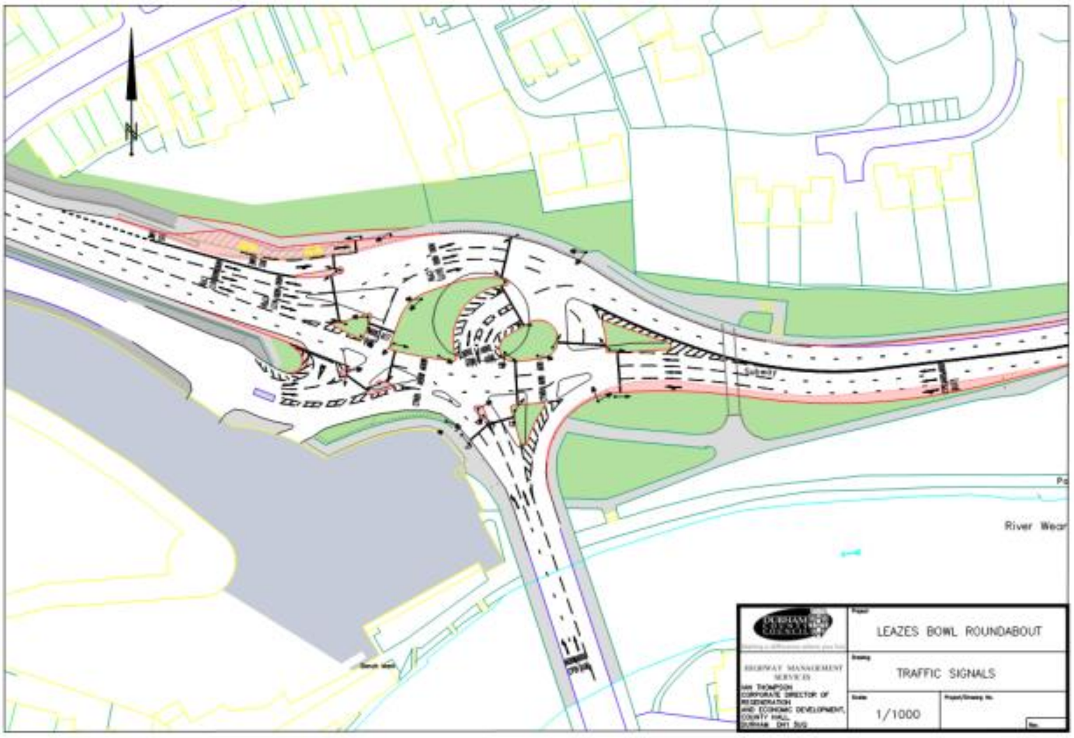



Figure 56. A690 Leazes Bowl Roundabout – Proposed Traffic Signal Layout.

Following the micro-scale findings from Chapter 5 it was concluded that the impacts of Durham Traffic Engineering Scheme would be more accurately assessed using an IEM approach to emissions modelling. As a number of key areas of Durham's AQMA are congested for significant periods of the day, congestion sensitive modelling was deemed vital for estimating the potential benefits of the scheme.

In order to model the proposed scenarios, appropriate changes were made to the existing Durham S-Paramics (SIAS, 2001) microsimulation model described in Chapter 5. Prior to modelling the scheme in microsimulation, the traffic signal design package Linsig v3 (Moore, 2011) was used to develop and optimise the signal operation of the proposed network (Optimised for 'Practical Reserve Capacity' (PRC)). The timings obtained from Linsig v3 were then transferred to the S-Paramics model and coded as fixed time signals. It is anticipated that some additional benefits either side of the peak network operation could be derived as a result of further optimisation using additional dynamic-signalisation tools such as PCMOVA or attempts to imitate SCOOT operation in the microsimulation. Such work could be incorporated into a future detailed design process should the scheme gain support for further development and inclusion in the Air Quality Action Plan.

Existing and proposed scheme microsimulation models were run for both AM and PM peak periods. Each microsimulation model was run ten times (total 40 runs), the resulting output files were processed through AIRE, and subsequently analysed using a bespoke software program (Section 3.3). The number of runs was chosen following variance analysis which showed the outputs stabilised within ten model runs (HCM, 2010). The overall average network results from both of the modelled peaks can be seen in Figure 57, Figure 58, and Table 25.

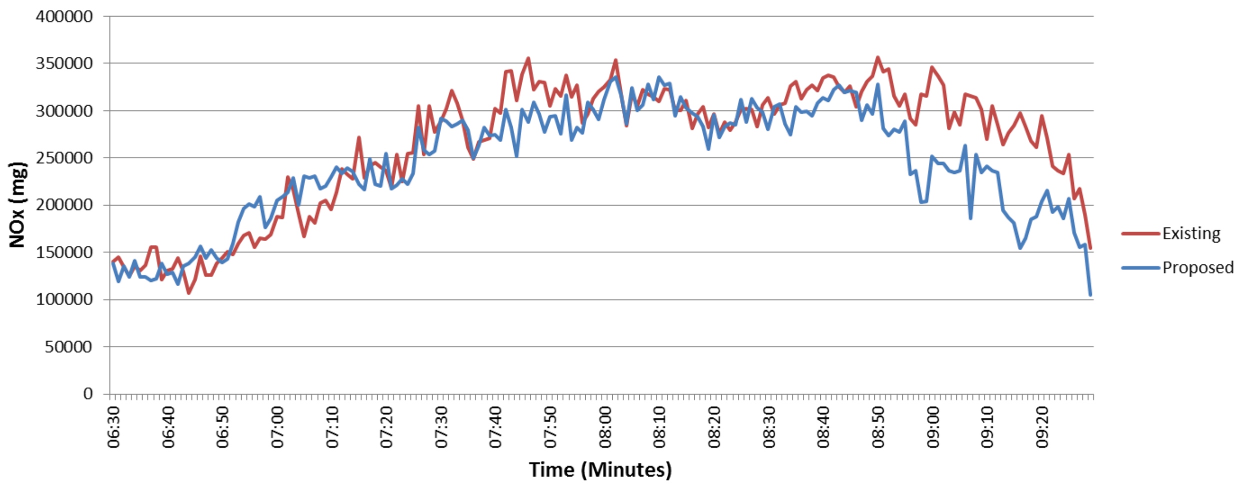



Figure 57. AM Peak Emissions Results (NOx) for existing situation and proposed scheme.

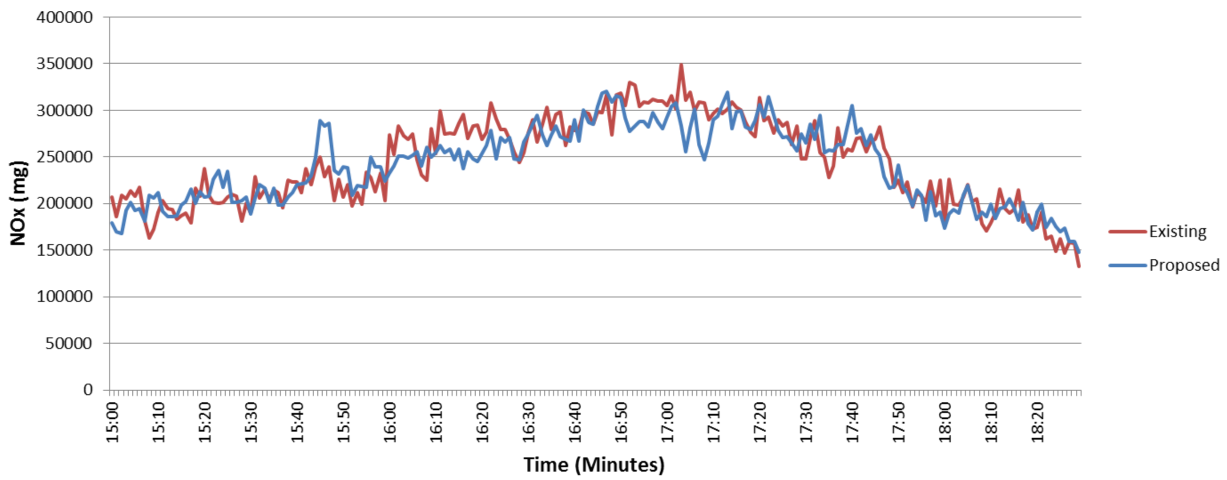



Figure 58. PM Peak Emissions Results (NOx) for existing situation and proposed scheme.

Table 25 Results from scheme appraisal, NOx emissions from AM and PM peak periods.

| **Peak** | NOx **(mg) Existing** | NOx **(mg) Proposed** | **Difference (mg)** | **Difference (%)** |
|---|---|---|---|---|
| AM | 47,387,363 | 43,913,854 | -3,473,510 | -7 |
| PM | 51,235,115 | 50,594,357 | -640,759 | -1 |

The results suggest that whilst the scheme shows a reduction of 7% in NOx emissions during the morning peak, the benefits are much lower at 1% for the evening peak. This may be due to the fact that the morning trips into the city are more constrained to the start times of employment and schools. The peak period during the evening peak is less stressed during the afternoon peak due to greater flexibility at the end of the day for businesses, industry and the school run.

### 6.2.1 **Air Quality Concentrations**

The emissions based approach to modelling air quality provided insight into the sources of air pollution and relative success of the traffic scheme. However, as in the previous micro-scale study it was important to gain an understanding of how those emissions interact with local topography, built environment and meteorology (Gastald et al., 2014). Therefore, ADMS dispersion modelling was again used to simulate the complex relationship between emissions estimates and outdoor air pollutant concentration (Hirtl and Baumann-Stanzer, 2007).

As with the micro-scale modelling in Chapter 5, 24 hour emissions estimates were produced for modelling, in order to allow the build-up and dispersal of emissions throughout the day to influence concentrations. Therefore, the existing and proposed scenario micro-simulation models were extended to cover a full 24 hour period and 'minute-by-minute' emissions results were aggregated into hourly values for all links in the network (Section 3.4.2). NOx values were converted to $NO_2$ using the 'NOx to $NO_2$' calculator version 3.1, published in September 2012 and these were then fed onto a dispersion model enabling comparison of concentrations from the existing network compared to the proposed scheme. The performance evaluation of the existing model is discussed in Section 5.2.2.

Analysis of annual mean $NO_2$ concentrations across key Durham receptors show that despite reporting an overall network reduction in emissions, the proposed scheme does not improve air quality across large areas of the study area (Figure 59).

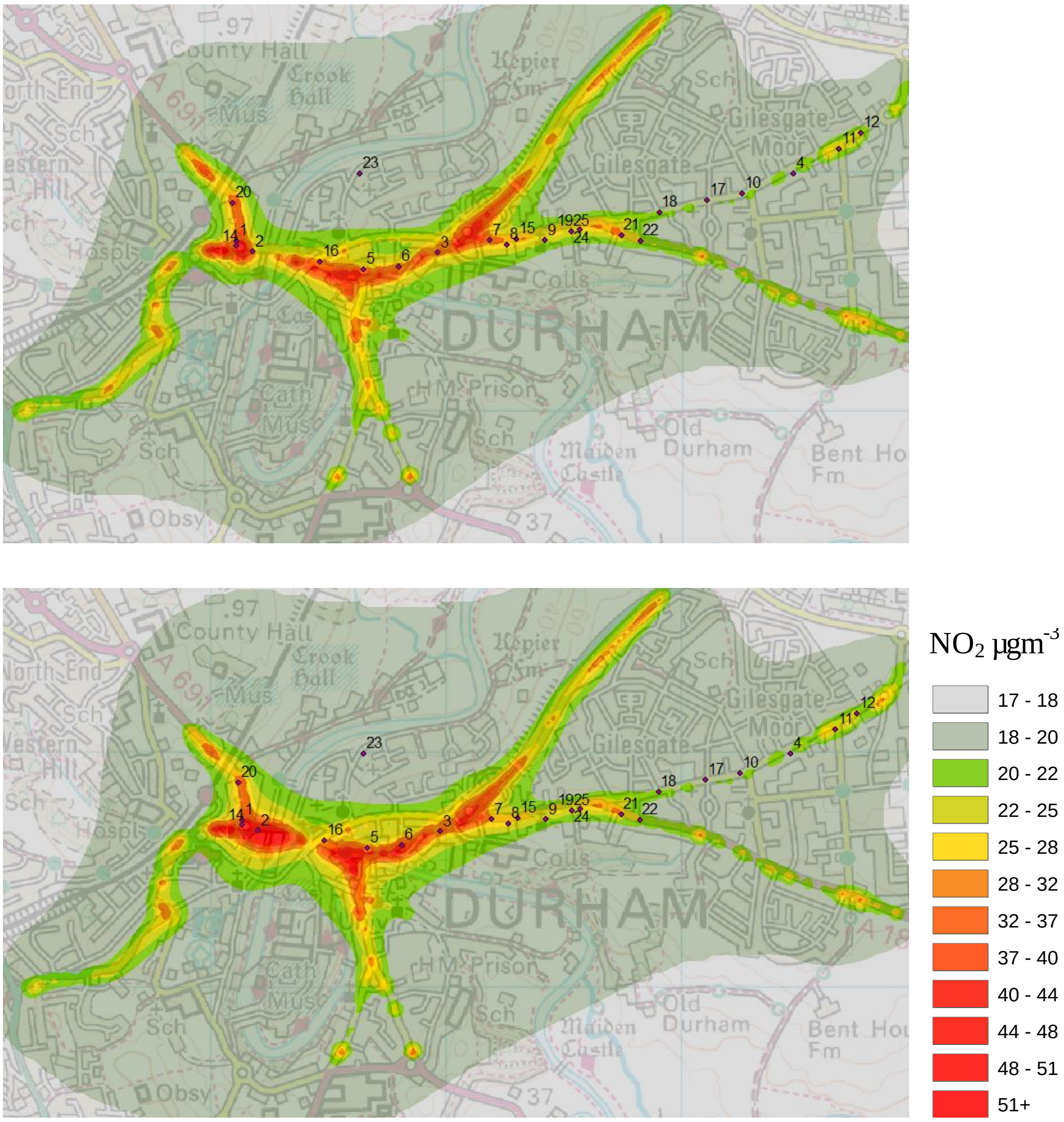



Figure 59. ADMS output ($NO_2$ $\mu gm^{-3}$) for 'existing' top, and 'proposed' bottom, scenarios.

However, there were improvements in air quality levels at 15 of Durham's 25 key receptors identified from the Durham County Council Local Air Quality Management Durham City Further Assessment report 2012 (See Table 26).

Table 26 Predicted Annual Mean $NO_2$ Concentrations, 2010, $\mu gm^{-3}$ across key Durham receptors.

| ID | Location | Within AQMA? | Modelled Air Quality Existing | Proposed | Diff. | % |
|---|---|---|---|---|---|---|
| 1 | 45 Highgate | Yes | 31.91 | 33.08 | 1.17 | 4 |
| 2 | Government Offices, Milburngate | Yes | 30.28 | 60.68 | 30.4 | 100 |
| 3 | Durham University (Gilesgate) | Yes | 31.14 | 32.00 | 0.86 | 3 |
| 4 | 81 Gilesgate Hill | Yes | 23.82 | 22.51 | -1.31 | -5 |
| 5 | 15 MarshallTerrace | Yes | 20.34 | 20.44 | 0.1 | 0 |
| 6 | 97 Claypath (Rear) | Yes | 23.96 | 23.64 | -0.32 | -1 |
| 7 | 22 Leazes Court (Leazes Road) | Yes | 27.83 | 28.14 | 0.31 | 1 |
| 8 | Ravensworth Terrace (Leazes Road) | Yes | 30.33 | 39.84 | 9.51 | 31 |
| 9 | 57 Gilesgate (Gilesgate Roundabout) | Yes | 56.79 | 33.24 | -23.55 | -41 |
| 10 | 5 Gilesgate (Gilesgate Roundabout) | Yes | 27.50 | 25.96 | -1.54 | -6 |
| 11 | 150 Gilesgate | Yes | 22.03 | 21.16 | -0.87 | -4 |
| 12 | Greenlane (Sunderland Road) | Yes | 22.81 | 22.43 | -0.38 | -2 |
| 13 | 1 Young Street (Sunderland Road) | Yes | 21.38 | 21.23 | -0.15 | -1 |
| 14 | 10 Sunderland Road | Yes | 19.37 | 19.30 | -0.07 | 0 |
| 15 | 37 Sunderland Road | Yes | 19.33 | 19.28 | -0.05 | 0 |
| 16 | 1 Sunderland Road | Yes | 24.96 | 25.49 | 0.53 | 2 |
| 17 | 10 Sunderland Road | Yes | 22.38 | 22.67 | 0.29 | 1 |
| 18 | Dragon Lane Junction | Yes | 26.09 | 26.68 | 0.59 | 2 |

| | | | | | | |
|---|---|---|---|---|---|---|
| 19 | 121 Gilesgate | Yes | 29.92 | 28.56 | -1.36 | -5 |
| 20 | Highgate | Yes | 28.30 | 30.17 | 1.87 | 7 |
| 21 | Gilesgate | Yes | 28.59 | 26.13 | -2.46 | -9 |
| 22 | Claypath | No | 31.93 | 30.86 | -1.07 | -3 |
| 23 | 56 McKintosh Court | No | 19.06 | 18.99 | -0.07 | 0 |
| 24 | 49 Sunderland Road | No | 20.17 | 20.14 | -0.03 | 0 |
| 25 | AQMA Monitor Gilesgate | Yes | 26.46 | 25.25 | -1.21 | -5 |

The overall impact on air quality was varied due to the critical location of some increases in emissions, particularly in the Milburngate area, which suffers from high concentrations of $NO_2$ in the existing scenario. However, other areas, for example, Gilesgate were significantly improved as a result of the Durham traffic engineering scheme (Table 26).

These results were presented to and acknowledged by DCC who utilised the findings in support of a DfT Local Major Transport funding application for the signalisation of Gilesgate and Leazes Bowl roundabouts.

### 6.3 Durham VKT Air Quality and Carbon targets

Recent research on the impact of road transport strategies on pollutant and carbon dioxide ($CO_2$) emissions has highlighted that substantial and arguably radical capacity restraint is required if UK air quality and climate change limit values and targets are to be achieved.

Given the growing concern that losing sight of air quality goals through the prominence of $CO_2$ and climate change agendas may result in failure to meet targets in both areas, this section explores the impact of reductions in VKT as both an air quality and carbon management strategy (EAC, 2010). Section 1.1 provides further background on the Climate Change Act in 2008 with respect to ($CO_2$) emissions and the interim targets proposed by the Committee on Climate Change.

The reductions required in VKT (over 2010 traffic flows) in Durham were investigated in order to meet both EU air quality limits and future carbon targets.

It is acknowledged that even maintaining VKT at 2010 levels is unlikely to happen and reductions from 2010 levels are improbable. However, it was the intention of this work to investigate, to the best of current knowledge, the level of VKT reductions which would be required to meet the various selected targets across the study area. This type of information is valuable in ensuring transport planners and network operators understand the true scale of the tasks in meeting legally bound targets.

The existing base-case was edited to reflect VKT restraint strategies imposed across the vehicle fleet. Emissions of $CO_2$, NOx and $NO_2$ were calculated and comparisons between the base-case and strategy were made in each case. In total five VKT restraint strategies were tested. Two of these strategies explored the fleet reduction required to meet legally binding future year $CO_2$ targets set out in the UK's carbon budgets; three strategies test the constraint required to meet the EU national annual mean $NO_2$ objective air quality target currently being exceeded in Durham under a variety of fleet emissions assumptions (Table 27). As $CO_2$ is not an air pollutant, its dispersion within the study area is not considered. Therefore $CO_2$ targets were assessed based on the analysis of emissions outputs from AIRE. Air quality targets required accurate assessments of air quality concentrations. Therefore, concentrations were obtained using dispersion modelling outputs following the method described in previous sections. It should be noted, strategies aimed at meeting air quality targets were recognised as being met when all key receptors recorded concentrations <40 $\mu gm^{-3}$. Therefore, whilst some areas of the network may still exceed 40 $\mu gm^{-3}$ this would not be considered an exceedance as per DEFRA guidance (DEFRA, 2016)

Table 27 VKT restraint strategies

| | VKT restraint strategy | Target |
|---|---|---|
| 1 | $CO_2$ 2020 | 37% Reduction relative to 1990 (18.5% relative to 2010 base-case) |
| 2 | $CO_2$ 2025 | 50% Reduction relative to 1990 (32% relative to 2010 base-case) |
| 3 | EU $NO_2$ (2010 Fleet) | Annual average mean $NO_2$ <40 $\mu gm^{-3}$ (assuming 2010 base-case vehicle fleet) All key receptors |
| 4 | EU $NO_2$ (2020 Fleet) | Annual average mean $NO_2$ <40 $\mu gm^{-3}$ (assuming 2020 vehicle fleet (COPERT 4v8.1)) All key receptors |
| 5 | EU $NO_2$ (2025 Fleet) | Annual average mean $NO_2$ <40 $\mu gm^{-3}$ (assuming 2025 vehicle fleet (COPERT 4v8.1)) All key receptors |

Figure 60 shows a flow diagram of the method used to model the strategies in this research. All strategies were modelled using the micro-scale modelling framework. VKT restraint strategies were implemented in 5% increments (e.g. 5%, 10%, 15% etc. total vehicle fleet reductions until targets are met) to allow the relationship between strategy and emissions or concentration change to be identified.

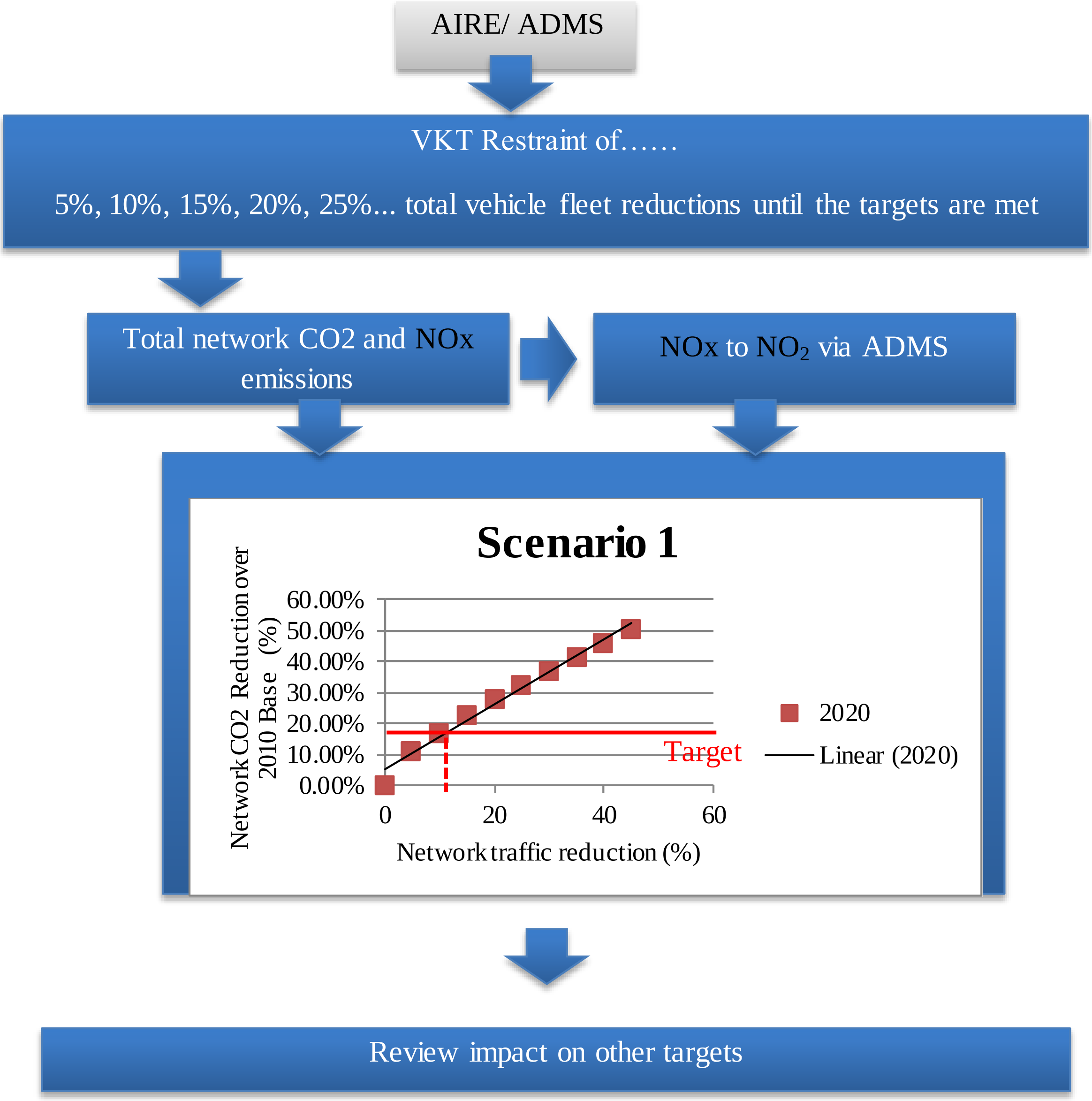



Figure 60. Strategy modelling method flow diagram.

The required reduction in vehicle fleet was identified for each of the VKT restraint strategies. The strategies that ensured all targets were met were identified; these strategies could be regarded as a win-win for air quality improvement and $CO_2$ reduction. Finally, those strategies that resulted in a trade-off were discussed.

Strategies 1 and 2, relating to carbon targets assumed the projected impact of a change in technology, fuel and vehicle type on emissions by adopting the projected vehicle fleets for the future target years. These assumptions were based on COPERT 4v8.1. Discussion on the accuracy of these future assumptions is discussed in the review of

‘Future Work’, Section 7.5. As Strategies 3-5 relate to a current air quality issue in Durham it was decided to model the VKT reduction required to meet the EU targets in the base-year, as well as in future years, harmonized with carbon targets so any synergies could be identified.

### 6.3.1 **VKT Strategy Results**

The results of the incremented VKT restraint strategy testing are presented in this section. Table 28 summarises the required vehicle fleet restraint in Durham if the considered targets are to be met. The results show the fleet reductions required to meet the targets, measured against both the 2010 base year traffic; as well as against projected traffic levels, given four of the five strategies refer to future year targets.

Predicted traffic growth was examined to establish the current best projections for future traffic growth in Durham. National Trip End Model (NTEM) (Version 6.2) forecasts and TEMPro (Trip End Model Presentation Program) (Version 6.2) software was used to obtain growth factors for the future target years examined in the research (Years 2020; 2025) (DfT, 2013). TEMPro and NTEM obtain growth projections using data from the National Transport Model (NTM). Following guidance from the DfT (2013) suitable settings were selected in TEMPro and ‘all purpose’ average weekday, origin/ destination, ‘combined modes’ traffic growth was identified for the Durham TEMPro geographical ‘ward’. These growth rates are presented in Table 28 along with the impact on required VKT restraint.

The current positive traffic growth rates provided in Table 28 show the true level of restraint required to meet the considered future targets; and highlight how fundamental planning and transport policy change is required if the investigated environmental targets are to be met.

Table 28 VKT restraint strategy results

| VKT strategy | | VKT restraint to meet target against 2010 base year (fleet % reduction) | VKT restraint to meet target against projected traffic growth (Growth rate in parenthesis) |
|---|---|---|---|
| 1 | $CO_2$ 2020 | 10% | 14% (4.7%) |
| 2 | $CO_2$ 2025 | 25% | 32% (7.0%) |
| 3 | EU $NO_2$ (2010 Fleet) | 50% | 50% (0.0%) |
| 4 | EU $NO_2$ (2020 Fleet) | 25% | 30% (4.7%) |
| 5 | EU $NO_2$ (2025 Fleet) | 15% | 22% (7.0%) |

As expected, the highest level of VKT restraint was required to meet the base year air quality ($NO_2$) target. Failures to meet this target in 2010 (Annual average mean $NO_2$ <40 $\mu gm^{-3}$) prompted the declaration of an AQMA in Durham in 2011. The results show that a dramatic 50% reduction in vehicle traffic would be required to meet this target in the 2010 base year (VKT Strategy 3). However, it is recognised that a plethora of alternative methods for meeting these targets could be considered at the local level; including, for example, variation in vehicle fleet compositions via a low emission zone (LEZ) (Holman et al, 2015). Strategies to meet some of these targets are currently under discussion; for example, by Durham's Air Quality Technical Working Group.

The most achievable target proved to be the 2020 $CO_2$ target set out in the UK Carbon Budget (37% Reduction relative to 1990 (18.5% relative to 2010 base-case)). However, as traffic growth in Durham (2010-2020) is currently predicted to rise by 4.7%, an overall net 14% VKT restraint still represents a significant turnaround in projected traffic growth figures.

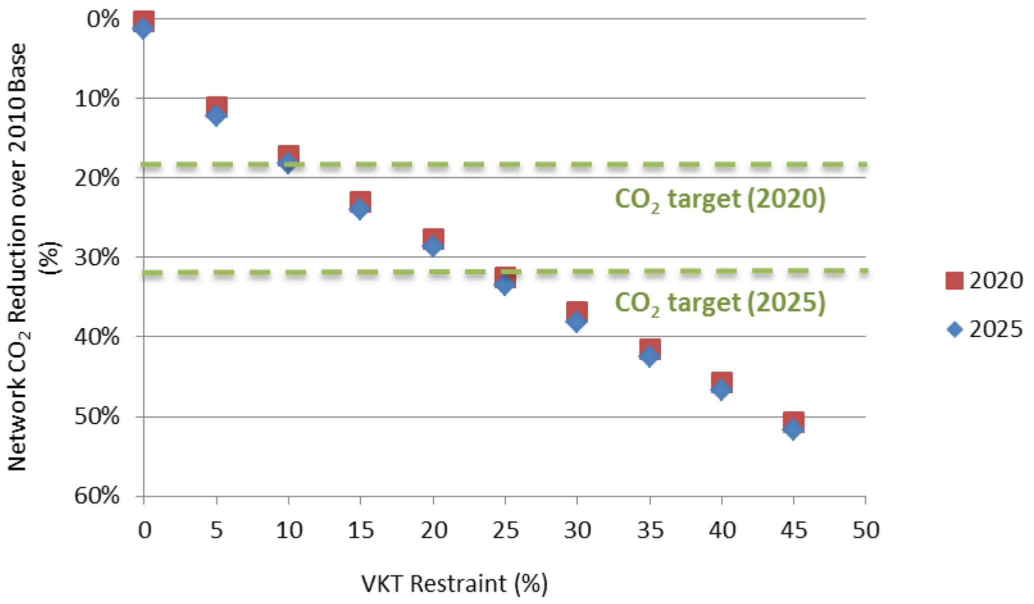



Figure 61. VKT Restraint to meet targets 1 and 2 (UK Carbon Budget $CO_2$ targets for years 2020/ 2025; assuming appropriate year vehicle fleet)

Figure 61 shows the results of the increment tests for Targets 1 and 2 (UK Carbon Budget $CO_2$ for years 2020/ 2025; assuming appropriate year vehicle fleet). The figure highlights that change to predicted vehicle fleet emissions between the years 2020-2025 has a relatively minor impact on total $CO_2$ outputs (<1%). It is also evident that due to reductions in congestion related emissions (and to a lesser extent due to predicted advancements in vehicle emissions output technology; based on analysis of the 2010 vehicle fleet result which showed <1% variation against 2020 outputs) predicted $CO_2$ emissions reductions are greater than their associated VKT restraint (i.e. 2020: 10% VKT reduction yields a 18.5% $CO_2$ reduction relative to 2010 base-case). However, the congestion impact lessens as the network becomes quieter with each incremented 5% VKT reduction. To meet the 2025 target a 25% VKT reduction is required to reduce $CO_2$ by 32% relative to the 2010 base-case.

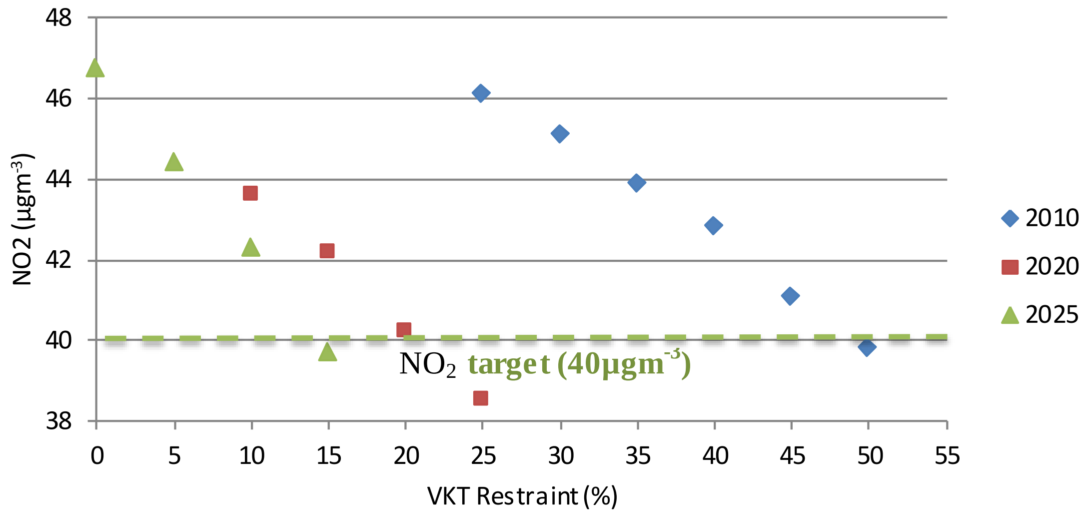



Figure 62. VKT Restraint to meet Targets 3-5 ($NO_2$ below 40µgm$^{-3}$ across all key receptors assuming 2010; 2020; 2025 vehicle fleets)

The VKT restraint required to meet Targets 3 to 5 is presented in Figure 62. In contrast to the $CO_2$ target results, the modelled vehicle fleet year has a substantial impact on the emissions, and consequent $NO_2$ concentration outputs. This finding is in agreement with a number of emissions inventories including COPERT 4v8.1. However, Carslaw and Rhys-Tyler (2013) and Anttila et al (2010) discuss the impact of primary $NO_2$ vehicle emissions on $NO_2$ concentrations and suggest caution in the prediction of future reductions in $NO_2$ emissions from road vehicles. Nonetheless the results are valid given the current limitations in predicting future year vehicle fleet emissions.

## 6.4 Discussion

This section deliberates the impact on EJ of both the Durham Traffic Engineering Scheme, and the VKT reduction strategies described in previous sections.

### 6.4.1 Impact of Durham Traffic Engineering Scheme on existing EJ concerns

Chapter 5, Section 5.2.3 provides the results from a micro-scale EJ study in Durham. The previous study by O'Brien et al (2013a) indicated that whilst there was no linear relationship between deprivation and air quality in Durham, there was evidence of environmental injustice in the distribution of air quality across 7471 households in the study area. It was found that the existing pattern of poor air quality in Durham negatively impacts two specific social groups as defined by Experian Mosaic data, namely student elements of Group G, *'Young, well-educated city dwellers'*; and Group C, *Wealthy people living in sought after neighbourhoods*.

These findings were determined by classifying households in Durham as being exposed to air quality ($NO_2$) 'above 25 µgm$^{-3}$' or '25 µgm$^{-3}$ and below.' 25 µgm$^{-3}$ was chosen to disseminate the total household population for two reasons. Firstly, as monitored data from DCC revealed the background $NO_2$ in Durham to be approximately 17 µgm$^{-3}$, 25 µgm$^{-3}$ represents a value where air quality is being influenced by local pollution but falls below the 40 µgm$^{-3}$ EU limit; secondly, this value allowed for a sufficiently large cohort of households in the 'poorer' air quality group. The Mosaic geo-demographic groups were then analysed to determine if there were was any evidence of environmental injustice amongst Mosaic groups.

Neither Mosaic Group G, nor Group C can be regarded as deprived social groups. In terms of deprivation they are ranked 7 and 13 out of the 15 groups respectively (with 1 being the most deprived group). However, whilst the findings are contrary to the perceived established relationship between air quality and socio-economic status, the findings are still representative of an environmental injustice. For example, Cutter (1995) defines EJ as equal access to a clean environment and equal protection from possible environmental harm irrespective of race, income, class, or any other differentiating feature of socio-economic status.

This section tests the impact of the Durham Traffic Engineering Scheme on the identified EJ concern, using an identical methodology to that applied in the existing scenario. Details of the methodology are omitted from this section and can be found in Section 5.2.

In keeping with the existing scenario Durham study analysis, household level Mosaic data was geocoded using Ordnance Survey Address-Point (Ordnance Survey, 2014) to provide coordinate information across 7471 households in the Durham study area (Figure 63). These data were entered in to ADMS-Urban to enable air quality concentrations to be generated for each address. This generated dataset was subsequently analysed to review the relationships between air quality and geodemographic status under the impact of the Durham traffic scheme.



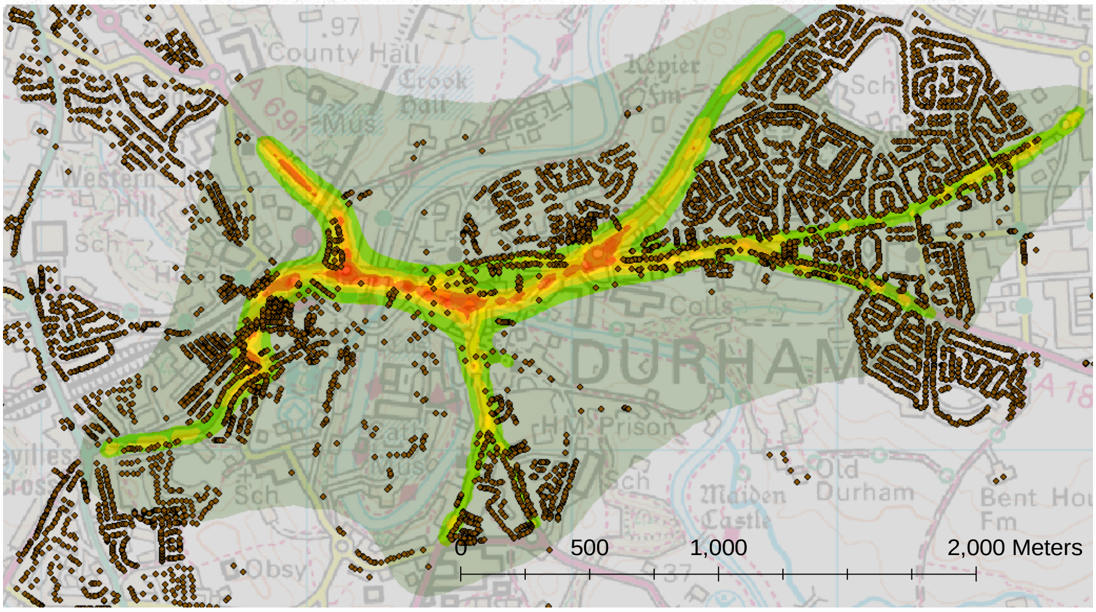



Figure 63. Location of 7471 residential property addresses in Durham study area

When investigating the impact of the Durham Traffic Engineering Scheme on EJ, chi squared statistics were again applied to the Mosaic geo-demographic group data to establish whether the proposed scheme influenced the environmental injustice amongst Mosaic groups (In the existing scenario Groups G and C were significantly over-represented in the 'above 25 μgm$^{-3}$' $NO_2$ in group).

Generally, the proposed traffic scheme had a negative impact in terms of EJ. Whilst no impact was seen on Group G households, the number of Group G households suffering from air quality levels above 35 μgm$^{-3}$ increased by 28% (from 39 to 50). However, the number of Group C households in the 'above 25 μgm$^{-3}$ category was not affected by the scheme. Furthermore, chi squared analysis showed statistically significant differences at the 95% confidence level between the expected and observed values indicating significant over-representation compared to the expected population of Group G (Table 29). Conversely, Group C was not significantly over-represented compared to the expected value. The result for Group C is in contrast to the existing scenario in Durham.

Chi squared results for the Existing network and Durham Traffic Engineering Scheme are summarised in Table 29.

Table 29 Chi squared results for ‘existing’ and ‘Durham Traffic Engineering Scheme’ scenarios

| Scenario | Chi squared test (Group verses ‘Other’) | | |
|---|---|---|---|
| | Group C (df = 1) | Group G (df = 1) | Group C and G (df = 2) |
| Existing Network | 5.961 | 188.113 | 217.870 |
| Air Quality management Traffic Engineering Scheme | 3.796 | 235.592 | 263.710 |

df = 1, p = 3.841 at 0.05 probability level

df = 2, p = 5.991 at 0.05 probability level

Three marked findings are evident from the analysis presented in Table 29. Firstly; in contrast to the base-case existing scenario, Group C did not show statistically significant differences at the 95% confidence level between the expected and observed values following the introduction of the proposed Durham Traffic Engineering Scheme. This indicates that the significant over-representation of Group C in the base-case is eliminated as a result of the scheme improving $NO_2$ concentrations across the study area. In contrast, Group G showed statistically significant differences at the 95% confidence level between the expected and observed values. This represents over representation of Group G in both the existing and proposed scenario. This result reveals that the identified instance of environmental injustice in the base-case remains, and the distribution of Durham’s air quality does not meet Cutter’s (1995) definition of equal access to a healthy environment. Finally, this statistically significant finding is also valid when considering the overall three group result.

### 6.4.2 **Impact of VKT strategies on existing EJ concerns**

This section considers the impact of the VKT reduction strategies on the spatial distribution of air quality in Durham. Details of the five VKT strategies are provided in Section 6.3.

Once again the approach used in the previous study by O'Brien et al.„ (2013a), was used to analyse the Mosaic geodemographic data and predicted $NO_2$ concentrations at 7471 households in the Durham study area. This analysis was completed for each of the five VKT strategy scenarios.

Within the Mosaic Public Sector database each of the 15 groups are assigned a Mosaic deprivation score (ranked 1 to 15, with 1 being the least deprived). Therefore, initial analysis of Mosaic deprivation score and modelled $NO_2$ at each of the households was performed to establish if a linear relationship existed between deprivation and air quality. As with the base-case Durham scenario presented in O'Brien et al.„ (2013a), $R^2$ values for each of five scenarios were found to be in the range 0.002 (+/- 0.001) confirming no significant relationship between deprivation and $NO_2$ level.

Following the initial analysis, households in Durham were again classed as being exposed to air quality ($NO_2$) 'above 25 $\mu gm^{-3}$' or '25 $\mu gm^{-3}$ and below'. In contrast to the base-case study the data showed that with any of the VKT strategies in place <50 households belonged to the 'above 25 $\mu gm^{-3}$ cohort (base-case >250 households). This was due to area wide reductions in $NO_2$ levels as a result of the reduced traffic levels across all scenarios. Nonetheless, chi squared statistics were applied to the Mosaic geo-demographic group data for each of the scenarios to establish whether the proposed strategies influenced the environmental injustice amongst the Mosaic groups.

To enable the chi squared analysis Mosaic group outputs were themselves categorised into one of three groups; *C, Wealthy people living in sought after neighbourhoods*; *G, Young, well-educated city dwellers'*; and *Other*. These groups were based on the numbers falling into the 'Above 25 $\mu gm^{-3}$' category and each group was individually tested for significant variance. The results of the chi squared analysis for each of the five strategies are summarised in Table 30.

Table 30 Chi squared results for the VKT reduction strategies

| | VKT reduction strategy | Chi squared test (Group verses 'Other') | | |
|---|---|---|---|---|
| | | Group C (df = 1) | Group G (df = 1) | Group C & G (df = 2) |
| 1 | $CO_2$ 2020 | 0.001 | 31.853 | 33.242 |
| 2 | $CO_2$ 2025 | 0.742 | 2.558 | 2.846 |
| 3 | EU $NO_2$ (2010 Fleet) | 0.360 | 8.118 | 9.627 |
| 4 | EU $NO_2$ (2020 Fleet) | 0.742 | 2.558 | 2.846 |
| 5 | EU $NO_2$ (2025 Fleet) | 0.204 | 11.821 | 11.899 |

df = 1, p = 3.841 at 0.05 probability level

df = 2, p = 5.991 at 0.05 probability level

A number of interesting findings are evident from the analysis presented in Table 30. Firstly, in contrast to the base-case result, Group C did not show statistically significant differences at the 95% confidence level between the expected and observed values. This indicates that the significant over-representation of Group C in the base-case is eliminated as a result of the VKT reductions improving $NO_2$ concentrations across all strategies.

In contrast Group G showed statistically significant differences at the 95% confidence level between the expected and observed values. This represents over-representation of Group G in three of the five strategies (Strategies 1, 3 and 5;Table 30). This result reveals that in these scenarios the identified instance of environmental injustice in the case-base remains, and the distribution of Durham's air quality does not meet Cutter's (1995) definition of equal access to a healthy environment.

Interestingly, Strategy 3, a 50% VKT reduction to meet an annual average mean $NO_2$ <40 $\mu gm^{-3}$ (assuming a 2010 base-case vehicle fleet), does not eliminate the identified EJ issue despite requiring the largest VKT reduction to meet the associated target. This shows the extent of the current EJ concern given current vehicle fleet emissions.

Furthermore, it reveals the dependence on projected improvements in $NO_2$ emissions from updated vehicle fleets to provide the solution to Durham's air quality issues.

Encouragingly two of the five strategies result in an environmentally just air quality distribution in Durham. Firstly, Strategy 2 UK's Carbon Budget $CO_2$ 2025 target, which requires a 50% reduction in $CO_2$ relative to 1990 (32% relative to 2010 base-case). In order to meet this target a 25% VKT reduction is necessary, assuming emissions estimates from the predicted 2025 vehicle fleet materialise. This level of VKT reduction also surpasses the reduction required in meeting the $NO_2$ target, assuming the correct vehicle fleet year. Similarly, Strategy 4, a 25% VKT reduction to meet an annual average mean $NO_2$ <40 $\mu gm^{-3}$ (assuming a 2020 vehicle fleet), also proves to be an environmentally just target in terms of distribution of Durham's air quality.

Strategy 5 does not eliminate the identified environmental injustice in Durham's air quality. This result highlights a limitation of the increment testing which can be observed in Figure 61. The Strategy 4 result shows that a 20% VKT reduction fails to meet the annual average mean $NO_2$ <40 $\mu gm^{-3}$ (assuming a 2020 vehicle fleet), as assuming this level of traffic reduction, a single key receptor records a concentration value of 40.23 $\mu gm^{-3}$. Therefore, following the 5% increment testing methodology the Strategy 4 target is only met with a 25% reduction, which results in the same receptor recording a concentration value of 38.51 $\mu gm^{-3}$ (over 1 $\mu gm^{-3}$ <40 $\mu gm^{-3}$). Therefore, due to the increment boundary, air quality across the study is higher than in Strategy 5, where a 15% VKT reduction results in a highest receptor concentration value of 39.68 $\mu gm^{-3}$ narrowly meeting the target concentration (0.32 $\mu gm^{-3}$ <40 $\mu gm^{-3}$). As a result finer increment testing may have a significant impact on the EJ assessment of the VKT strategies as more accurate reduction requirements are recorded.

## 6.5 Summary

A novel approach to modelling road networks has been successfully applied to test air quality and carbon management VKT strategies in Durham.

The results of this research show that the Durham Traffic Engineering Scheme proposed by DCC does not significantly improve air quality in Durham. Furthermore, the introduction of the scheme would exacerbate an existing EJ issue identified in the distribution of Durham's air quality.

Additionally, substantial levels of VKT restraint are required if the considered targets are to be met. This is of considerable concern given current predictions of further traffic increases in Durham for the foreseeable future, which will only exacerbate the existing failings.

A considerable 50% reduction in VKT would be required to meet the air quality ($NO_2$) target in the 2010 base year. By 2025, assuming an optimistic attitude to the success of future technology in reducing vehicle fleet emissions, a 15% VKT reduction would be required to meet the annual mean objective for $NO_2$ concentrations in Durham. However, given predicted traffic growth of a further 7%, a net 22% VKT reduction is needed.

Given current planning and transport policy regarding demand management it is unlikely that this level of VKT reduction will be achieved. Nonetheless this research has resulted in a greater understanding of the extent of the problems faced in managing the air quality issue in Durham. Furthermore, it is hoped this information may influence the outcomes of Durham's Air Quality Action Plan by working with Durham's Air Quality Technical Working Group of which the author is a member.

Similarly, whilst the 2020 UK Carbon Budget target was highlighted as the most achievable of the considered targets, a net 14% VKT reduction is still required (with a further 18% VKT reduction to ensure the 2025 UK Carbon Budget target is met).

Additionally, it has been established that the required reductions in VKT to meet two of the five considered targets eliminates an identified EJ issue in the existing spatial distribution of Durham's air quality. Overall, assuming an optimistic attitude to the success of future vehicles fleet technology, a 25% reduction in 2010 traffic levels by 2025 can be regarded as the most positive target for Durham's transport planners. This level of traffic eliminates the identified EJ issue in Durham, and meets both air quality and future carbon targets ensuring a synergised strategy for a sustainable future. This level of VKT restraint is also required to meet these requirements in 2020.

Finally, given current concerns over the ability of future technologies to reduce emissions from vehicular transport, it should be noted that alternative solutions to solving current environmental goals are likely to be required, even if dramatic VKT restraints are achieved in Durham.

CHAPTER 7

# 7. Summary and Conclusions

In this chapter a summary of the research is presented. Conclusions are drawn from the work conducted and future research is suggested.

## 7.1 Summary

This research presents a robust air quality modelling framework to map the EJ of the spatial distribution of air quality; and the impact of air quality management measures on existing EJ concerns. To assist in this goal, a modelling approach has been developed which enables the assessment of traffic management solutions that may create only subtle changes in the traffic flow regimes; and accurately assesses the impact of a reduction in vehicle kilometres travelled (VKT). The use of microsimulation traffic modelling in conjunction with an instantaneous emissions model (IEM) allows a congestion sensitive analysis of the network to be performed (Atjay et al., 2008). Findings from micro-scale modelling have revealed that the use of an IEM to calculate emissions as an input for air quality dispersion modelling significantly improved the performance of the dispersion modelling when measured against monitored data.

Utilising these advances in emissions and air quality modelling in conjunction with the innovative use of Mosaic Public Sector profile data has enabled a more accurate picture of the existing EJ of the spatial distribution of air quality to be established than in previous EJ studies. Furthermore, using these processes in a modelling framework has enabled the impact of air quality management measures on addressing EJ concerns to be more accurately assessed than using traditional methods.

This research has established that, at a city level, there is no linear relationship between air quality and deprivation in the North East cities of Durham, Newcastle and Gateshead. However, analysis of geodemographic data at the household and postcode levels has provided evidence of environmental injustice in air quality across all three study areas.

Additionally, this research has explored the impact of reductions in VKT as a proposed air quality management measure. Thereby, the reductions required in VKT (over 2010 traffic flows) in one study area, Durham, have been established in order to meet both EU air quality limits and future carbon targets.

Incremented 5% VKT reduction changes were made to the base-case 2010 scenario until all considered targets were met. Based on a 2010 vehicle fleet, a 50% reduction in traffic through Durham's AQMA is required to meet all EU air quality targets. Similarly, a 25% reduction in VKT is required assuming a 2020 vehicle fleet, and by 2025 a 15% reduction in VKT would ensure Durham met its air quality targets. Moreover, a 10% reduction in VKT by 2020, and 25% reduction by 2025 would ensure carbon dioxide ($CO_2$) reductions across the study area equal to those set out in the carbon budget.

Furthermore, it has been established that the reductions in VKT to meet both EU air quality limits and future carbon targets eliminates the identified EJ issue in Durham. Moreover, if future VKT is constrained to 2010 levels, the spatial distribution of air quality will be environmental just in both the 2020 and 2025 assessment years.

## 7.2 Conclusions and Recommendations

The following key findings can be drawn from the research carried out:

1. There is evidence of environmental injustice in air quality across all three study areas (Significant over representation of key Mosaic groups in areas of higher air pollution).

2. There is no significant linear relationship between air quality and deprivation in cities of Durham/ Gateshead/ Newcastle.

3. Durham's air quality problem cannot be solved by signalising Gilesgate and developing a signals strategy to 'gate' traffic. Whilst the scheme led to a reduction in overall vehicle emissions, the effect on air quality was not

significant due to the spatial location of the emissions reductions and the presence of ‘hot spots’ of pollution in Durham’s AQMA. Similarly, this proposed scheme did not significantly influence environmental justice.

4. Durham County Council’s traffic scheme to signalise Gilesgate does have a recordable impact on overall emissions for the study area, with total NOx reductions of 7% and 1% across the AM and PM peak traffic periods.

5. The use of an IEM to model emissions increases the accuracy of air quality predictions when compared to traditional average speed based approaches.

6. A **50%** reduction in 2010 traffic levels is required to meet all air quality EU criteria in Durham based on current vehicle fleet. This reduction also eliminates the identified EJ issue.

7. A **25%** reduction in 2010 traffic levels is required to meet all air quality EU criteria in Durham based on 2020 vehicle fleet. This reduction also eliminates the identified EJ issue.

8. A **15%** reduction in 2010 traffic levels is required to meet all air quality EU criteria in Durham based on 2025 vehicle fleet. This reduction also eliminates the identified EJ issue.

9. A **10%** reduction in 2010 traffic levels is required to meet 2020 $CO_2$ target in Durham based on 2020 vehicle fleet. This reduction also eliminates the identified EJ issue <u>BUT</u> fails to meet all air quality EU criteria.

10. A **25%** reduction in 2010 traffic levels is required to meet 2025 $CO_2$ target in Durham based on 2025 vehicle fleet. This reduction also eliminates identified EJ issue <u>AND</u> meets all air quality EU criteria. Thereby, assuming an optimistic attitude to the success of future vehicle fleet technology a **25%** reduction in 2010 traffic levels can be regarded as the most positive target for Durham’s transport planners.

11. The majority of previous EJ studies in the UK examine EJ using socio-economic indexes and other data sources which ensure it is only practical to analyse data in terms of linear relationships between the variables. This research highlights the importance of considering nonlinear relationships. This expands on findings by Mitchell at al. (2015) who discussed that deprivation is not automatically the most appropriate demographic measure against which to assess environmental inequity. In addition to supporting this conclusion, this research adds that it is also important to assess environmental inequalities specific to key population types not defined by conventional linear indexes.

## 7.3 Policy Implications of the Research

It is important to consider the policy implications of the findings presented in this research. Additionally, given the successful application of a modelling framework able to assess the EJ implications of air quality strategies that may create only subtle changes in the traffic flow regimes, consideration of how government, local authorities and other practitioners should look to adopt these methods to assist in the development of future air quality guidance and strategy is sought.

In the UK, legislation is already in place that requires the assessment of equality in transport. The Equality Act (2010) combined a number of current laws and provided a single piece of legislation designed to provide protection against direct and indirect discrimination in a number of areas, including transport. Of most direct relevance to this research is the requirement to have due regard to reducing the inequalities of outcome which result from socio-economic disadvantage during strategic decision making. The Equality and Human Rights Commission has published guidance for service users about transport and travel which provides information on how the Equality Act (2010) applies to transport users as a member of the public (Equality and Human Rights Commission, 2016a and 2016b). This guidance covers equality discrimination for direct users, as well as outlining the strategic aim of tackling inequalities in access to appropriate transport.

The Department for Transport, Transport Analysis Guidance (TAG) TAG UNIT A3 Environmental Impact Appraisal (DfT, 2015a) provides direct guidance on assessing air quality impacts in acknowledgement of the requirement to tackle air pollution and inequalities. This guidance is aimed directly at local authorities and practitioners and largely governs the approach and level of work conducted to satisfy the Department for Transport when assessing a new transport scheme. In keeping with the majority of transportation guidance the primary focus of the assessment is on the quantification and monetarisation, so as to capture the economic disbenfit of the air pollution, particularly in recognition of its impact on health. However, separate WebTAG guidance TAG UNIT A4.2 also includes consideration of the distributional impacts of changes in air quality. This guidance directly acknowledges that "poor air quality problems are often experienced in areas of deprivation, in which people already suffer relatively poor health, health problems can be exacerbated for such deprived communities" (DfT, 2015b). Furthermore, the guidance briefly outlines some of the EJ themes discussed in Section 2.5 of this thesis, namely that "the poor air quality experienced in some areas of low car ownership is a clear issue of social justice as these people experience the impacts of car use, but do not themselves have access to a car" (DfT, 2015b). The guidance concludes that the user should concentrate the analysis of changes in air quality on the impacts on households in areas of relatively high income deprivation as a proxy.

The presence of existing guidance in this field reflects the large body of work described throughout this thesis and highlights the importance of being able to address these issues with greater accuracy and understanding. Three key findings from this research have direct implications for the current distributional assessment guidance.

Firstly, the guidance suggests that the analyst should map, using GIS, variations in socio-demographic data using a variety of traditional sources at the LSOA and ward level e.g. Census 2011, Index of Multiple Deprivation (IMD), and the Income Deprivation domain of the English Indices of Deprivation (IoD) 2010. As highlighted in the literature review, the majority of previous EJ studies in the UK examine EJ using socio-economic indices and other data sources at the LSOA level (Mitchell et al, 2015). However, as discussed in the pilot study in Chapter 4 (Section 4.4.2) LSOAs cover a minimum population of 1000, and a mean population of 1500. In contrast, Durham's AQMA covers a residential population of approximately 750. Furthermore, according to the 2010 Detail Air Quality Assessment completed by DCC only 44 households in

Durham are identified as being exposed to $NO_2$ concentrations above 40µg/m3 (Durham County Council, 2010a). Whilst it is acknowledged that LSOA scale analysis may be more appropriate for some of the UKs larger cities, typically the number of receptors within the UKs AQMAs is in the order of 10 to 50 houses or other area of interest (Chatterton, 2008). In this context the use of comparatively large area LSOAs appears a relatively blunt tool for assessing deprivation. This research has highlighted EJ concerns present in the population which could not be identified through analysis at the LSOA level. The importance of appropriate scale in assessing EJ concerns is therefore a key note for guidance and policy implementation.

Secondly, in common with the majority of previous EJ studies highlighted in Section 2.5.3, WebTAG assessment guidance is limited to the analysis of linear relationships, often between a single suggested variable (e.g. income). This research highlights the importance of considering nonlinear relationships and assessing environmental inequalities specific to key population types not defined by conventional linear indexes such as the IMD. Whilst it is acknowledged that it is often difficult to obtain socio-economic data, guidance and policy must be broad enough to recognise the complex interlinked impacts of transport and air quality issues and the diversity of those groups who may be disadvantaged or impacted negatively as a result of associated problems.

Finally, under current WebTAG guidance, whilst the base case analysis of environmental distributional impacts suggests a quantitative review of the available data, the suggested appraisal methodology when determining the impact of the intervention is entirely qualitative. For example, the analyst is provided with a general system for grading of distributional impacts for each of the identified social groups (Figure 64).

| Table 5 General system for grading of DIs for each of the identified social groups | |
|---|---|
| **Impact** | **Assessment** |
| Beneficial and the population impacted is significantly greater than the proportion of the group in the total population | Large Beneficial ✓✓✓ |
| Beneficial and the population impacted is broadly in line with the proportion of the group in the total population | Moderate Beneficial ✓✓ |
| Beneficial and the population impacted is smaller than the proportion of the group in the total population | Slight Beneficial ✓ |
| There are no significant benefits or disbenefits experienced by the group for the specified impact | Neutral |
| Adverse and the population impacted is smaller than the proportion of the population of the group in the total population | Slight Adverse × |
| Adverse and the population impacted is broadly in line with the proportion of the population of the group in the total population | Moderate Adverse ×× |
| Adverse and the population impacted is significantly greater than the proportion of the group in the total population | Large Adverse ××× |

Figure 64. General system for grading of distributional impacts (TAG Unit A4.2, (DfT, 2015b).

It is recognised that given current guidance must reflect a workable approach and available resource, a simple qualitative assessment of the likely impact of a transport strategy or scheme on the population has advantages in avoiding complexity and allowing for quick comparisons across options. Additionally, the local authority or practitioner must also consider other issues when completing a distributional impact assessment, for example, user benefits, noise, affordability, accessibility. In this context constructing a matrix, qualitative approach to the assessment is a logical and valid attempt to address the issues.

However, given the importance of air quality as a problem, and the extents of the EJ issues in exposure to air pollution described in this research and the wider body of work, there is strong justification for a need for additional quantitative work in assessing distributional impacts when making important decisions on future transport schemes and strategies. This is a key policy recommendation identified as a result of this research.

Whilst, in its current form, the modelling framework described in this research is both data and time intensive, with further additional research, programming, licensing and resource, it would doubtlessly be possible to create a modular based programme to mechanise the bespoke links between the utilised software programmes and data sources. Such a tool could provide a practical, quantitative approach for local authorities and other practitioners to assess the EJ of the spatial distribution of air quality for typical transport schemes. It is suggested that this work should be completed, either in the research environment, or through industry, to the benefit of local authorities.

When considering how government should use the information from this thesis for policy implementation it is also important to consider the wider complexity of transport equity analysis (Litman, 2012).

As discussed in Section 2.5, there are several interpretations of what constitutes equity and a wide number of interlinked impacts to consider. For example, this research has identified that in order to meet the air quality targets and establish an environmentally just distribution of air quality in Durham, significant reductions in traffic levels are required. However, this result or research does not provide answers to how a reduction should be brought about, and indeed, if doing so is achievable in an equitable way.

Access to transport is in itself a basic human provision, and often one subject to unfairness (Walker, 2012). Discussing equality and the elimination of road deaths, Acheson (1998) suggests that seeking elimination of deaths from collisions and transport related pollution might involve travel restrictions, creating a new set of deaths associated with a lack of available transport needed for accessing goods and services such as healthcare. Similarly, policy objectives for air quality must consider the wider transport planning context and recognise that, whilst an important indirect health impact, solutions to air quality problems may exacerbate other issues or inequalities.

Exploring this subject Mullen et al. (2014) present an outline for the application of equal concern to transport policy, planning and law state. Their account of equality applied to transport involves two non-hierarchical priorities. Firstly, "that deaths associated with transport should be minimised, subject to the condition of avoiding inequalities in life-threatening risk" (Mullen et al., 2014), and secondly, that people are entitled to access to a means of travel. However, this paper also identifies that focusing on minimising death may not be sufficient unless we also consider whether some defined groups of people (e.g. in particular geographical locations or age groups) will be more exposed than others to risks of death. Therefore, a further condition is suggested that attempts to reduce inequalities in the levels of physical risk to which different people are subject are also required.

Following these priorities in the application of equal concern in an air quality context leads to many of the same conclusions. Namely, that access to means of transport does not mean that all modes should be protected by policy; and one individual's entitlement may be limited by the equal entitlement of others (Mullen et al., 2014). Policy which supports fewer deaths and great equality associated with transport could be regarded as the ultimate goal, and recognising that there is both individual and collective responsibility to use less polluting nodes in addressing air pollution and wider transport issues the ultimate solution.

It is recognised that it is far beyond the scope of this PhD to identify measures which might be effective in reducing vehicle traffic. However, the research findings can be used to identify relevant policy areas and to further guide policy development towards solutions that minimise inequality. If social justice is to be the real driver for air quality improvement its assessment must be completed with this goal in mind, and interventions suitably scored against these wider objectives of equality in transport model planning and policy.

This research suggests a 25% reduction in 2010 traffic levels can be regarded as the most positive target for Durham's transport planners. The above understanding should be applied in achieving this target. Namely, solutions to this reduction should be sought that minimise inequality. This, it is suggested, requires the promotion of use less polluting modes including walking and cycling (Higgins, 2005; Mullen et al., 2014).

In recent years air quality has gained significant momentum as a political issue, largely as a result of the increased understanding of the health implications of air pollution, and also as a result of high profile news events such as the emissions scandal and London's attempts to meet its statutory air quality targets (Section 2.3).

Low Emission Zones (LEZs) are one measure identified by the UK government's air quality plan to reduce harmful emissions in specific areas by discouraging more polluting vehicles from entering areas where air quality is poor. In much the same way, LEZs have proliferated throughout Europe, particularly during the past decade (Charleux, 2014).

However, whilst there is strong evidence that the introduction of LEZs has brought positive effects on reducing air pollutant concentrations (Holman et al, 2015; Jiang et al, 2017), recent analysis using household-travel survey data to assess how a projected LEZ in Grenoble, France could affect individuals' mobility, has found evidence that the probability that people will be affected by the LEZ is related to their social group (Charleux, 2014). Charleux (2014) concludes that his findings may represent social injustice dependant on interpretations in terms of social justice and, on the reference population considered. Similarly, Cesaroni et al. (2012) found that whilst the LEZ traffic policy in Rome was effective in reducing traffic-related air pollution, most of the health gains were found in well-off residents.

Research in this area highlights that despite the propagation of LEZs, there is disparity in policy designed to improve air quality; and suggests a need for renewed attention in understanding the wider policy implications with regards to social justice.

In the UK a review of The London Low Emission Zone Feasibility Study, prior to the introduce of London's LEZ, reveals that whilst there was some discussion of the potential of a low emission zone to affect car ownership for low-income groups as a result of the exclusion of older vehicles, there is no specific evidence of impact analysis regards social exclusion or exacerbation of social injustice (Watkiss et al., 2003).

Given its successful testing of a range of transport schemes and strategies, the modelling framework presented in this research could doubtlessly be utilised to model the implementation of a LEZ. This work could be used to assess how an LEZ could be implemented to provide a positive impact to both air quality and social justice. Government should work to ensure that air quality policy gives greater consideration of social justice, and guidance for local authorities is extended require more robust quantitative assessment of social justice impacts so that transport schemes which benefit EJ may be prioritised.

Finally, giving thought to the future of UK air quality policy, there is little doubt that the rise and momentum behind air quality as an important UK and global issue has reached an important stage in more recent years, arguably following decades of reduced attention since the relative success of the Clean Air Act 1956, following a similar phase of sustained media and public attention.

The review of the implications of the UK's likely exit from the European Union for air quality legislation (Section 2.3) would suggest that there is limited risk of disruption given that even the UK's existing Air Quality Objectives are said to be at least as stringent as the limit values of the relevant EU Directives (Upton, 2017).

Nonetheless, there is potential for focus to shift further away from meeting specific EU set air quality limit values, in favour of more objective regulation under the Air Quality (England) Regulations 2000. Whilst it is vital that efforts to reduce air pollution are maintained, this represents an opportunity for new policy to provide renewed emphasis on objective goals which, it is argued and demonstrated by this research, should include a drive for promoting transport solutions and strategies which enhance social equality in the spatial distribution of air quality.

## 7.4 Contribution to Academic Research and Practice

1) The strategy modelling approach developed in this research allowed substantive conclusions to be drawn. The findings of this study clearly identified evidence of environmental injustice in air quality across all three study areas. The majority of previous EJ studies in the UK examine EJ using socio-economic indices and other data sources which ensure it is only practical to analyse data in terms of linear relationships between the variables. This research highlights the importance of considering nonlinear relationships.

2) The modelling methodology developed in this research provided a quantified increase in the accuracy of air quality predictions when compared to traditional average speed based approaches.

3) The conclusion of this research provided evidence that Durham's Air Quality problem cannot be solved by signalising Gilesgate and developing a signals strategy to 'gate' traffic. Nonetheless, a quantified benefit to air quality was identified.

4) The conclusion of this research represents an evidence base on which to build new and more aggressive traffic reduction strategies in Durham if 2025 $CO_2$ targets are to be met.

5) The importance of this research was acknowledged by Durham County Council who used the findings in support of a DfT Local Major Transport funding application for the signalisation of Gilesgate and Leazes Bowl roundabouts. Whilst independent modelling was conducted by commissioned Consultants in respect of traffic journey time benefits delivered as a result of the scheme; the council also wanted to explore the impact on air quality of signalising a key part of the network, particularly given its location within Durham's AQMA.

Whilst the findings of this research demonstrated that the overall impact of the scheme on air quality was variable depending on the location of some increases in emissions, it was able to demonstrate reductions of 7% and 1% in NOx emissions during the morning peak and evening peaks respectively, and improvements in air quality at 15 out of 25 of the identified receptors (Section 6.2).

Similarly, DCC considered the research findings with regards to the impact of Durham Traffic Engineering Scheme on existing EJ concerns (Section 6.4). However, given that the findings indicated the scheme did not significantly improve (or exacerbate) the EJ of the spatial distribution of air quality, the contribution to an enhanced understanding of the scheme outcomes was acknowledged, but the results were not used specifically in the funding bid.

Following the completion of the research work the Local Major Transport bid subsequently proved successful. As of September 2017 the newly upgraded and signalised Gilesgate roundabout was switched on as part of the installation of the

SCOOT system works. Work currently programmed in 2018 should see the completion of the scheme including the signalisation of Leazes Bowl roundabout (Durham County Council, 2017). This project demonstrates the successful application of the modelling framework and underlines the novelty and importance of the findings reported in this thesis. In addition the impact of this research has been immediate given how the outputs already have been used in the real world environment. It is hoped that with additional support this work can be repeated for future projects as discussed in the following section.

## 7.5 Future Work

1) The emissions factors used in this research have since been updated as they were considered not to be representative of real world emissions. For example, AIRE, does not contain factors for Euro 5 or 6 vehicles. New factors released are considered interim by the UK government, and a number of uncertainties are in existence. The Emissions Factor Toolkit (EfT) received a relatively significant update in November 2017, in part in response to the emissions scandal related to Volkswagen Group although much of the work in response to this is still ongoing (Section 2.2) (DEFRA, 2017b). Updates that have been made include emission rates changes for year 2005-2030 including increase in emissions rates for diesel cars and vans; fleet composition updates to reflect new vehicle sales; emissions scaling factors; and technology conversions for hybrid vehicles. More specific updates to NOx and PM speed emission coefficient equations are taken from the EEA COPERT 5 emissions calculation tool, along with better representation of failure rates; and outputs of fraction of primary $NO_2$ of NOx emissions where input f-$NO_2$ data is provided.

   Also, COPERT 5 was released in November 2015 (COPERT 4v8.1 was used in this research). Whilst the updates from COPERT 4 are not expected to have significant impact on the overall outputs of this research, particularly given that significant fuel/ energy consumption and emissions factor updates are still under development, the results from this research should be updated and adjusted as required. This could be achieved via correction factors in most instances.

However, it should be noted that AIRE itself, which was used to calculate emissions in Chapter 5 and 6 of this research has not received further update. Given AIRE's reliance on PHEM based lookup tables; a substantial update would require funding for a large scale project, similar to the original ARTEMIS project, to obtain updated dynamometer data. Alternatively, data could be sought from a rolling programme adding new vehicle types/emission point maps into the databases as they appear. However, a more practical approach to updating AIRE, could involve applying 'conformity/ adjustment factors' and create new AIRE tables. It is suggested that this process should be carried out to allow for more accurate future assessments as the presence of Euro 5 and 6 vehicles increases with time. The resources to perform this work and recalibrate the model using supplementary on-road results is significantly outside what could be deemed achievable in this research.

2) Advances in other areas, particularly work concerning emissions rates for hybrid, plug-in-hybrid, diesel-hybrid, and electric cars could eventually alter the course of the findings of this research. Sales in hybrid and electric vehicles are at a critical stage with cumulative year-on-year uptake of hybrid and electric vehicles increasing from 20,000 in 2013 to more than 135,000 in 2017 (DfT, 2017). As a result, the predictions for future vehicle fleets are likely to have a high margin of error. Furthermore, given the increased rate in uptake of electric vehicles in very recent years it could be argued that the decision to review transport strategies that exercise VKT restraint risks becoming obsolete, as policy may instead look to promote electric vehicles at the expense of modal shift. Future work to explore expansion of electric vehicles at the expense of VKT constraint should be completed. However, there is a large body of work in support of the wider benefits of modal shift and the author hopes that policy supporting soft measures and other none polluting modes continues to prevail (Higgins, 2005; Mullen et al, 2013).

3) If this research was to be repeated, the 2010 base year could be revised provided that suitable data is made available across all subject areas (e.g. transport/ air quality / health and environmental justice modelling).

4) The use of national data to define vehicle fleet composition in this is considered a limitation. The outcome of the application of local fleet data would provide an interesting comparator.

5) Additional research, programming, licensing and resource would enable the creation of a modular based programme to mechanise the bespoke links between the software programmes and data sources used in this research. Such a tool could provide a practical, quantitative approach for local authorities and other practitioners to assess the EJ of the spatial distribution of air quality for typical transport schemes.

6) Further to discussion on personal air quality exposure studies in Section 2.11, it is recognised that existing air quality policy, which identifies specific receptors as geographical locations, such as houses or schools, leads itself to geographical based research such as that conducted in this thesis. However, in reality personal exposure to air quality is influenced by significantly more than home address or place of school or occupation. This is noted as an area of weakness for this work. Future work to try to incorporate personal exposure experiments to social justice studies should be explored given the limits of science and monitoring mean there are significant uncertainties in the air quality people actually experience (Walker 2012).

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# 9. Appendices

## 9.1 Appendix A

Table A1 Types of Air Pollutant

Types of Air Pollutant/ Green House Gas (Sources: Various (for reference only)).

| Pollutant | Info | Government Air Quality Indicator? | Health Impacts | Source |
|---|---|---|---|---|
| Sulphur dioxide (SO2) | Acidic gas, formed by the oxidation of sulphur impurities in fuels during combustion processes. | ✓ | SO2 is a respiratory irritant and can cause constriction of the airways of the lung. This effect is particularly likely to occur in people suffering from asthma and chronic lung disease. The effects of the gas on the lung's airways can occur very rapidly, making exposure to short-term peak concentrations important. Long-term exposure to lower levels has also been linked with adverse effects on lung function. Typical ambient short-term and longer-term concentrations within the UK towns and cities are generally below peak limit values set by the European Commission to protect human health. In 2009 the maximum hourly mean across all sites in the AURN (including traffic sites) was 271 µg m-3, compared to the limit value of 350 µg m-3 (which may be exceeded up to 24 times in the calendar year). The annual average across all sites in the AURN (including traffic sites) was just 3 µg m-3. Highest concentrations are likely to occur in residential areas with a high proportion of solid fuel use for domestic heating: also close to industry or large combustion plant under adverse weather conditions, which occasionally result in plume grounding.<br><br>SO2 is also a precursor to secondary particulate matter (PM), and therefore contributes to the ill-health effects caused by PM10 and PM2.5. The health effects of SO2 and PM are closely linked, the individual effects of each pollutant only being quantifiable in the last 10 years or so. There is potential for damage to ecosystems at high levels, including degradation of chlorophyll, reduced photosynthesis, raised respiration rates and changes in protein metabolism. Deposition of pollution derived from SO2 emissions can contribute to acidification of soils and waters and subsequent loss of biodiversity, often at locations far removed from the original emissions. | A very high proportion (approximately 85%) of UK SO2 emissions originate from power stations and industrial sources, although these emissions are generally released at height by chimneys to achieve effective dispersion under normal conditions. Another important source of ground level SO2 has historically been solid fuel use in domestic heating systems. As the use of coal and other solid fuels for domestic heating has decreased over the last 30-40 years with the penetration of natural gas into the UK's domestic central heating system stock, SO2 emissions and atmospheric concentrations have decreased.<br><br>Previously diesel cars – problem solved by catalytic converters? |
| Nitrogen Oxides | | | | |
| Nitrogen dioxide ($NO_2$) | Redish brown toxic gas, sharp biting odour. Nitrogen dioxide is a large scale pollutant, with rural background ground level concentrations in some areas around 30 µg/m3, not far below unhealthy levels. Nitrogen dioxide plays a role in atmospheric chemistry, including the | ✓ | Long-term exposure to NO2 at concentrations above 40– 100 µg/m3 causes adverse health effects. NO2 exposures outdoors is complicated by the fact that in most urban locations, the nitrogen oxides that yield NO2 are emitted primarily by motor vehicles, making it a strong indicator of vehicle emissions (including other unmeasured pollutants emitted by these sources). NO2 (and other nitrogen oxides) is also a precursor for a number of harmful secondary air pollutants, including nitric acid, the nitrate part of secondary inorganic aerosols and photo oxidants (including ozone). The situation is also complicated by the fact that photochemical reactions take some time. | The most important sources of NO2 are internal combustion engines (motor vehicles), thermal power stations and, to a lesser extent, pulp mills. Butane gas heaters and stoves are also sources. The excess air required for complete combustion of fuels in these processes introduces nitrogen into the combustion reactions at high temperatures and produces nitrogen oxides (NOx). Limiting NOx production demands the precise control of the amount of air used in combustion. Nitrogen dioxide is also produced by atmospheric nuclear tests.<br><br>Motor vehicles make the largest contribution to long-term ground level concentrations in urban areas, and the highest NOX levels in UK cities generally occur at kerbside locations in urban areas. In the presence of sunlight, nitrogen oxides can react with Volatile Organic Compounds (VOC) to produce |

| Pollutant | Info | Government Air Quality Indicator? | Health Impacts | Source |
|---|---|---|---|---|
| | formation of tropospheric ozone. | | Human chamber studies have shown that in allergic subjects NO2 can enhance the effect of allergens. Bronchial reactivity also was increased in the presence of NO2 (390). These studies show effects at levels twice or more of the current guideline value.<br><br>By affecting the immune cells in the lungs, it can also increase susceptibility to respiratory infections. Recent epidemiological studies have shown consistent associations between long term exposure to NO2 and lung function in children as well as with lung function and respiratory symptoms in adults. These effects cannot be attributed to NO2 exposure per se. The epidemiological studies provide some evidence that long-term NO2 exposure may decrease lung function and increase the risk of respiratory symptoms.<br><br>In general, individuals with asthma are expected to be more responsive to short-term exposure to inhaled agents, when compared to individuals without asthma (WHO, 2003).<br>At very high concentrations, such as may occur in certain industrial accidents, NO2 can cause severe, sometimes fatal, lung damage. At ambient levels (which are very much lower) it acts as an irritant,<br><br>It has been difficult to determine the direct, individual health effects of NO2 at ambient concentrations because it is emitted from the same sources (notably traffic) as other pollutants such as PM. Ambient levels of NO2 away from busy roads in the UK are typically below the Limit Values set by the European Union to protect human health. Occasionally the hourly mean Limit Value is breached, as explained in section 5. Close to busy roads, short and long-term average concentrations are higher particularly in locations with poor dispersion characteristics such as street canyons. Concentrations above the Air Quality Directive Limit Values for human health have been observed in large cities in the UK, although this is not a problem specific to the UK and is common in many other European countries.<br><br>High levels of NOX can also have an adverse effect on vegetation, including leaf or needle damage and reduced growth. Deposition of pollutants derived from NOX emissions contribute to acidification and/or eutrophication of sensitive habitats leading to loss of biodiversity, often at locations far removed from the original emissions. NOX also contributes to the formation of secondary particles and ground level ozone, both of which are associated with | photochemical pollutants including ozone. Nitrogen dioxide can be further oxidised in air to acid gases such as nitric acid, which contribute to the production of acid rain. |

| Pollutant | Info | Government Air Quality Indicator? | Health Impacts | Source |
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| | | | ill-health effects. Ozone also damages vegetation. | |
| Nitric oxide (NO) | Nitric oxide (common name) or nitrogen monoxide (systematic name) is a chemical compound with chemical formula NO. Nitric oxide is rapidly oxidised in air to nitrogen dioxide. | × | NO is not considered to be of concern with respect to human health. NO2 is the more harmful species. | See $NO_2$ |
| Particulate matter (PM) | Complex mixture of organic and inorganic substances. Particles can be primary (emitted directly to the atmosphere) or secondary (formed by the chemical reaction of other pollutants in the air such as SO2 or NO2). | ✓ Both PM10 and PM2.5 | Particles found in ambient air range in size from a few nanometres (nm, or 10-9 m) to several hundred micrometres (µm, or 10-6 m) in diameter. Particle size is usually expressed in terms of its aerodynamic diameter. Two fine size fractions of particulate matter are measured in UK national monitoring networks: PM10 and PM2.5. PM10 is the mass concentration (expressed in µg m-3) of PM that is generally less than 10 millionths of a metre (10 µm) in diameteri. PM2.5 refers to the mass concentration of particles less than 2.5 µm in diameter.<br><br>Fine particles are the main focus in air quality monitoring, as fine particulate matter can penetrate deep into the airways, carrying surface-absorbed harmful compounds into the lungs, increasing the risk of health effects. In most urban environments, both coarse (>PM2.5) and fine particles (<PM2.5) are present, but the proportion of particles in these two size ranges is likely to vary substantially between cities depending on local geography, meteorology and specific PM sources.<br><br>The range of health effects associated with PM is broad, but is predominantly related to the respiratory and cardiovascular systems. All population is affected, but susceptibility to the effects of PM may vary with health or age. The risk for various outcomes has been shown to increase with exposure, with both short-term and long-term exposure being important. There is little evidence to suggest a threshold below which no adverse health effects would be anticipated, but effects are unlikely to be noticed even by sensitive individuals below about 60 µg m-3 for PM10. In 2009, the average number of days per site with PM10 concentrations in the 'Moderate' band or above was four (at urban sites). Annual mean PM10 concentrations for urban background and roadside sites are also reported annually as a Government Air Quality Indicator. At urban background sites, the annual mean PM10 concentration for 2009 was 19 µg m3; at roadside sites it was slightly higher at 22 µg m-3. | Particles may arise from a wide variety of sources, man-made or natural. The main source of particles is combustion i.e. traffic and power stations. Other man-made sources include quarrying and mining activities, industrial processes, dust from construction work and particles from tyre and brake wear. Natural sources include wind-blown dust, sea salt, pollens, fungal spores and soil particles. |

| Pollutant | Info | Government Air Quality Indicator? | Health Impacts | Source |
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| | | | Ambient levels of PM are below the long-term limit values for the protection of human health throughout the UK. In the UK, the short-term, daily mean limit value for the protection of human health is exceeded in central London only. (i.e. over 35 bad days per year – this is leading to legal action and potentially resulting in fines of up to £300m, unless it stepped up efforts to comply with air quality rules.<br><br>A new EU Directive is introducing additional PM2.5 objectives targetting the exposure of the population to fine particles. These objectives are set at the national level and are based on the average exposure indicator (AEI). | |
| Benzene | Benzene is an organic chemical compound | ✓ | Benzene is a recognised human genotoxic carcinogen which attacks genetic material. As a result there is no absolutely safe threshold below which no adverse health effects are anticipated. Nevertheless, European Limit Values have been proposed below which, risks of health effects are exceedingly small, and the UK is compliant with these levels for benzene in all outdoor non-occupational locations. | Ambient benzene concentrations arise primarily from road transport and the domestic combustion of wood and non-smokeless fuel. Benzene is naturally broken down by chemical reactions in the atmosphere over a period up to several days; as a result outdoor benzene concentrations tend to correlate well with road networks and traffic density patterns, concentrations are now low due to the introduction of catalytic converters on car exhausts. |
| Carbon Monoxide (CO) | Also called carbonous oxide, is a colourless, odourless and tasteless gas which is slightly lighter than air. | ✓ | In closed environments the concentration of carbon monoxide can easily rise to lethal levels.<br><br>The health threat from carbon monoxide at low levels is most serious for those who suffer from cardiovascular disease, such as angina pectoris. At much higher levels, carbon monoxide can be poisonous. Visual impairment, reduced work capacity, reduced manual dexterity, poor learning ability and difficulty in performing complex tasks are all associated with exposure to carbon monoxide. | Carbon monoxide is present in small amounts in the atmosphere, chiefly as a product of volcanic activity but also from natural and man-made fires (such as forest and bushfires, burning of crop residues, and sugarcane fire-cleaning). The burning of fossil fuels also contributes to carbon monoxide production. Petrol engines used to emit significant amounts of CO but concentrations are now very low due to the introduction of catalytic converters on car exhausts. The UK is compliant with European Limit Values for CO in all outdoor non-occupational locations.<br><br>Carbon monoxide occurs dissolved in molten volcanic rock at high pressures in the Earth's mantle. Because natural sources of carbon monoxide are so variable from year to year, it is extremely difficult to accurately measure natural emissions of the gas.<br><br>Carbon monoxide is produced from the partial oxidation of carbon-containing compounds; it forms when there is not enough oxygen to produce carbon dioxide (CO2), such as when operating a stove or an internal combustion engine in an enclosed space. In the presence of oxygen, carbon monoxide burns with a blue flame, producing carbon dioxide. People are more likely to be exposed to dangerous concentrations of CO indoors. The main indoor sources are incorrectly installed, poorly maintained or poorly ventilated cooking and heating appliances such as gas fires, gas boilers and wood burning stoves. Cigarette smoke is also a major source of exposure. |
| Ozone ($O_3$) | A secondary pollutant gas, formed by photochemical reactions in the lower atmosphere (the troposphere). In the stratosphere (part of the upper | ✓ | O3 is an oxidising agent and acts as an irritant, producing inflammation of the respiratory tract. At high concentrations O3 irritates the eyes, nose, and throat, causing coughing and discomfort whilst breathing. Exposure to elevated levels over several hours can lead to damage of the lining of the airways. This is followed by inflammation and | In the lower atmosphere however, O3 is an air pollutant. It is produced by the photochemical effect of sunlight on oxides of nitrogen and volatile organic compounds produced by motor vehicles and industry. These reactions take place over periods of several hours or even days. Once formed, O3 can travel long distances, accumulate and reach high concentrations often far away from the sources of the original pollutants. NOX emitted in cities reduces local O3 |

| Pollutant | Info | Government Air Quality Indicator? | Health Impacts | Source |
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| | atmosphere) O3 is formed by the action of ultraviolet light on oxygen molecules. This produces the ozone layer and at this level the gas has a beneficial effect by absorbing harmful ultraviolet radiation from the sun. | | narrowing of the airways and increased sensitivity to stimuli such as cold air and exercise. This is called ―airway hyper-responsiveness‖. There is a wide variation in individuals‘ sensitivity to the effects of O3. During pollution episodes, high levels of O3 may exacerbate asthma or trigger asthma attacks. Some non-asthmatic individuals might also experience discomfort when breathing, particularly if they are exercising vigorously outdoors.<br><br>At urban sites, the average number of days in 2009 with _Moderate‘ or worse air quality – at which sensitive individuals may notice effects – caused by ozone was just six14. However, at rural sites the average was 32 days per site in 200914 (the Indicators report does not provide a breakdown by pollutant but states that the _vast majority‘ of rural air pollution is caused by ozone.) Since 1997, the average number of days per site with _Moderate‘ or worse air quality has been greater at rural sites than at urban sites – and the majority of such days at rural sites are due to ozone14.<br>Controls limiting the emissions of VOC from road transport and large scale industry have lead to a reduction in emissions of precursor species and the magnitude and frequency of ozone pollution episodes. However, under favourable conditions ozone pollution episodes and exceedences of the European Target Values for human health protection do occur in the UK, particularly when stable anticyclonic atmospheric conditions persist over the UK and northern Europe. Typically these conditions are only experienced a handful of times a year, most commonly over the summer months. | concentrations as NO reacts with O3 to form NO2. This means that O3 precursors generated in countries with large traffic and industrial emissions may affect less polluted countries, and that levels of O3 in the air are often higher in rural areas than urban areas. For example, it is often the case that when O3 levels are elevated in the South East of England, much of the O3 has originated in continental Europe. O3 concentrations are greatest in the summer (usually on hot, sunny, windless days) and lowest in the winter months. |
| Lead (Pb) | A main-group element with symbol Pb (from Latin: plumbum) and atomic number 82. Lead is a soft, malleable poor metal. It is also counted as one of the heavy metals. | ✓ | Exposure to high levels in air may result in toxic biochemical effects which have adverse effects on the kidneys, gastrointestinal tract, the joints, reproductive systems, and acute or chronic damage to the nervous system. There is evidence of impaired intellectual development in young children arising from long-term exposure to lead at elevated levels well in excess of the EU limit value of 0.5 µg m-3. | The majority of lead emissions arise from industry, in particular non-ferrous metal smelters. |
| Heavy Metals | Arsenic (As)<br>Cadmium (Cd)<br>Nickel (Ni) | ✓<br>Arsenic (As)<br>Cadmium (Cd)<br>Nickel (Ni) | Nickel may cause damage to the kidneys, inhibit reproductive ability, and result in respiratory problems.<br><br>Exposure to arsenic dust causes respiratory irritation and it is believed to be a carcinogen.<br><br>Inhalation of cadmium present in airborne particulate matter results in a build-up of cadmium in the kidneys that can cause kidney disease. Exposure to cadmium is also likely to increase the risk of lung cancer in humans. | Nickel is found in ambient air as a result of releases from oil and coal combustion, nickel metal refining, sewage sludge incineration, manufacturing facilities, and other sources.<br><br>Arsenic is emitted into the atmosphere as arsenic trioxide in the form of particulate matter. The primary source of arsenic emissions to the air in the UK is the combustion of coal and other fossil fuels, and also industrial processes which use arsenic.<br><br>Mercury is released to the air by human activities, such as coal burning, use of mercury in industrial processes, and the release of mercury in dental |

| Pollutant | Info | Government Air Quality Indicator? | Health Impacts | Source |
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| | | | High levels of mercury in the bloodstream of unborn babies and infants may impede the development of the nervous system.<br><br>Health effects of these metals are only expected at elevated levels in excess of the European Values. | fillings from crematoria. |
| Polycyclic Aromatic Hydrocarbons (PAHs)<br><br>Benzo[a]pyrene (B[a]P) | Benzo[a]pyrene (B[a]P) is used as a 'marker' for a group of chemical compounds known as polycyclic aromatic hydrocarbons (PAHs). | ✓ | Polycyclic aromatic hydrocarbons are a large group of persistent, bio-accumulative, organic compounds with toxic and carcinogenic effects.<br><br>Studies of occupational exposure to PAHs have shown an increased incidence of tumours of the lung, skin and possibly bladder and other sites. Lung cancer is most obviously linked to exposure to PAHs through inhaled air. Individual PAHs vary in their ability to induce tumours in animals or humans. | Produced from a wide range of industrial, chemical and combustion processes.<br><br>The main sources of ambient B[a]P include road transport, domestic solid fuel use and activities at iron and steel plant. A major source of human exposure is also cigarette smoke. |
| Carbon dioxide ($CO_2$) | CO2 is a trace gas comprising 0.039% of the atmosphere. Carbon dioxide is colourless. At low concentrations, the gas is odourless. At higher concentrations it has a sharp, acidic odour. | × | Carbon dioxide content in fresh air (averaged between sea-level and 10 kPa level, i.e., about 30 km altitude) varies between 0.036% (360 ppm) and 0.039% (390 ppm), depending on the location.<br><br>Prolonged exposure to moderate concentrations can cause acidosis and adverse effects on calcium phosphorus metabolism resulting in increased calcium deposits in soft tissue. Carbon dioxide is toxic to the heart and causes diminished contractile force.<br><br>Toxicity and its effects increase with the concentration of CO2, here given in volume percent of CO2 in the air:<br><br>1% can cause drowsiness with prolonged exposure.<br>At 2% it is mildly narcotic and causes increased blood pressure and pulse rate, and causes reduced hearing.<br>At about 5% it causes stimulation of the respiratory center, dizziness, confusion and difficulty in breathing accompanied by headache and shortness of breath. Panic attacks may also occur at this concentration.<br>At about 8% it causes headache, sweating, dim vision, tremor and loss of consciousness after exposure for between five and ten minutes.<br><br>Due to the health risks associated with carbon dioxide exposure, the U.S. Occupational Safety and Health Administration says that average exposure for healthy adults during an eight-hour work day should not exceed | Carbon dioxide is produced when any form of carbon or almost any carbon compound is burned in an excess of oxygen.<br><br>Almost all CO2 **emissions (i.e. man made)** (about 96.5%) come from fossil fuels use. The 3 types of fossil fuels that are used the most are coal, natural gas and petroleum. When fossil fuels are combusted, the carbon stored in them is emitted almost entirely as CO2.<br><br>The three main sectors that use fossil fuels are:<br><br>Transportation<br>Utilities<br>Industrial production<br><br>Inventory of U.S. Greenhouse Gas Emissions and Sinks (2008), EPA.<br><br>Human activities such as the combustion of fossil fuels and deforestation have caused the atmospheric concentration of carbon dioxide to increase by about 35% since the beginning of the age of industrialisation.<br><br>Through Earth history the amount of carbon dioxide in the atmosphere has varied significantly. The Earth's early atmosphere was probably composed mostly of carbon dioxide. At that time, the natural greenhouse effect would have been very strong, trapping much more heat than today, but billions of years ago the Sun was not as hot. During the last few hundred million years, the concentration of atmospheric carbon dioxide has generally been declining. In the most recent geological past it has been only a trace gas making up a few hundred parts per million of the gases in the atmosphere.<br><br>At the end of the last Ice Age 14,000 years ago, the level of carbon dioxide in the air increased about |

| Pollutant | Info | Government Air Quality Indicator? | Health Impacts | Source |
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| | | | 5,000 ppm (0.5%). The maximum safe level for infants, children, the elderly and individuals with cardio-pulmonary health issues is significantly less. For short-term (under ten minutes) exposure the limit is 30,000 ppm (3%). Carbon dioxide concentrations exceeding 4% are immediately dangerous to life and health although physiological experiments show that such levels can be tolerated for some time.<br><br>These figures are valid for pure carbon dioxide. In indoor spaces occupied by people the carbon dioxide concentration will reach higher levels than in pure outdoor air. Concentrations higher than 1,000 ppm will cause discomfort in more than 20% of occupants, and the discomfort will increase with increasing CO2 concentration. Higher CO2 concentrations are associated with occupant health, comfort and performance degradation. ASHRAE Standard 62.1-2007 ventilation rates may result in indoor levels up to 2,100 ppm above ambient outdoor conditions. Thus if the outdoor ambient is 400 ppm, indoor levels may reach 2,500 ppm with ventilation rates that meet this industry consensus standard. | 50%. Scientists believe this may explain some of the rise in global temperatures that occurred at that time. Following this global climate transition the atmospheric carbon dioxide concentration remained fairly constant at about 280 parts per million until the end of the 18th century. Since then, man-made emissions of carbon dioxide from burning fossil fuels, deforestation, waste incineration and the manufacture of cement have upset the balance between natural sources and sinks of carbon dioxide. Consequently, the concentration of carbon dioxide in the air has increased to about 370 parts per million, and is continuing to increase at a rate of about 1.2 parts per million each year. This level of carbon dioxide is higher than at any other time in the last 160,000 years.<br><br>Man-made carbon dioxide accounts for only 3.225% of global CO2.<br><br>Other natural sources include volcanoes/ bush fires |
| Methane ($CH_4$) | Methane is both a common naturally occuring chemical and is manufactured by man. Methane is the second most important "greenhouse gas" (after carbon dioxide) resulting from human activities. Releasing it to the atmosphere is thought to contribute to global warming.<br><br>Other names:<br><br>Natural gas; methyl hydride; marsh gas; biogas; fire damp; R 50 (refrigerant) | × | Excessive exposure to methane may affect the brain.<br><br>Methane gas build-up from landfill sites is a potential explosion hazard. In the past this has resulted in a few temporary evacuations of residents in housing estates built on top of old landfill sites that have not sufficiently vented the methane.<br><br>The main impact of methane on the environment is as a greenhouse gas, leading to global warming. Over the last two centuries, methane concentrations in the atmosphere have more than doubled, largely due to human-related activities. Methane is the second most important greenhouse gas, after carbon dioxide. Although less emissions of methane are emitted into the environment the Global Warming potential of Methane is 21 times that of CO2, over 100 years. | Methane is a trace constituent of the atmosphere. Man made sources include natural gas extraction and transportation (methane is the main component of natural gas) waste disposal, agriculture and coal mining. Methane is also released in significant amounts by marshland, rice paddies and by ruminant animals (e.g. cattle, sheep) and termites. |
| Nitrous oxide ($N_20$) | Commonly known as laughing gas. Colourless non-flammable gas, with a slightly sweet odour and taste. N2O is a greenhouse gas with tremendous global warming potential (GWP). When compared to carbon dioxide (CO2), N2O has | × | Health impacts at outdoor pollution levels are negligible. | N2O is produced naturally in the soil during the microbial processes of nitrification and denitrification.<br>In 2008, agriculture contributed 6.1% of the total U.S. greenhouse gas emissions and cropland contributed nearly 69% of total direct nitrous oxide (N2O) emissions<br>Production of nylon, and the burning of fossil fuel in internal combustion engines (20-30%). |

| Pollutant | Info | Government Air Quality Indicator? | Health Impacts | Source |
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| | 310 times the ability to trap heat in the atmosphere. Nitrous oxide also causes ozone depletion. A new study suggests that N2O emission currently is the single most important ozone-depleting substance (ODS) emission and is expected to remain the largest throughout the 21st century. | | | |
| Hydrofluorocarbons (HFCs) | HFCs are man-made chemicals containing the element fluorine used predominantly as refrigerants and aerosol propellants. They are colourless, odourless and chemically unreactive gases. They are "greenhouse gases" - releasing them to the atmosphere is thought to cause global warming. They are primarily being used as replacements to ozone damaging CFCs and HCFCs. | × | Excessive exposure to some hydrofluorocarbons may affect the brain and heart. The Environment Agency aims to ensure that environmental exposures are too low to harm human health. | Major sources of HFC release include refrigeration and air conditioning equipment, HCFC 22 manufacture, some specialist aerosols and newer Metered Dose Inhalers (e.g. for asthma). There are no natural sources of HFCs.<br><br>There was limited usage before the Montreal Protocol and subsequent phase out of the related CFCs and HCFCs. Emissions of HFCs from the UK are rising as they continue replace CFC and HCFC usage. In 1997 the annual emission of HFCs was over 3 million kg, mainly from their use as refrigerants.<br><br>HFCs are mainly used as substitutes for CFCs and HCFCs (ozone depleting substances) that are being phased out under the 1987 Montreal Protocol. Major usage is as refrigerants in refrigeration and air conditioning equipment and as propellants in industrial aerosols and newer MDIs (Metered Dose Inhalers, e.g. for asthma). Minor uses include foam-blowing (e.g. making plastic foams for food packaging), solvent cleaning and in some fire extinguishing systems.<br><br>Hydrofluorocarbons (HFCs) are a group of compounds containing carbon, fluorine and hydrogen (unlike HCFCs, which also contain chlorine). They are generally colourless and odourless gases at environmental temperatures and for the most part chemically unreactive.<br><br>The main impact of HFCs on the environment is as greenhouse gases, leading to global warming. Because they are only released in relatively small amounts current concentrations are estimated to represent only around 2.2% of the total UK global warming contribution. They have very high global warming potentials (100-3000 times that of carbon dioxide), however these are lower than the CFCs and HCFCs they replace. The concept of Global warming potential has been developed to compare the ability of each greenhouse gas to trap heat in the atmosphere relative to another gas. Due to their stability they have fairly long atmospheric lifetimes (tens to hundreds of years). |
| Perfluorocarbons (PFCs) | PFCs are man-made chemicals, colourless, odourless, non-flammable and unreactive gases. | × | Excessive exposure to perfluorocarbons may affect the brain and heart. The Environment Agency aims to ensure that environmental exposures are too low to harm human health. | Perfluorocarbons (PFCs) are fluorocarbons, compounds derived from hydrocarbons by replacement of hydrogen atoms by fluorine atoms. PFCs are made up of carbon and fluorine atoms only, such as octafluoropropane, perfluorohexane and perfluorodecalin. |

| Pollutant | Info | Government Air Quality Indicator? | Health Impacts | Source |
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| | | | | PFCs are extremely potent greenhouse gases, and they are a long-term problem with a lifetime up to 50,000 years.[28] In a 2003 study, the most abundant atmospheric PFC was tetrafluoromethane.[28] The greenhouse warming potential (GWP) of tetrafluoromethane is 6,500 times that of carbon dioxide, and the GWP of hexafluoroethane is 9,200 times that of carbon dioxide.[29] Several governments concerned about the properties of PFCs have already tried to implement international agreements to limit their usage before it becomes a global warming issue. PFCs are one of the classes of compounds regulated in the Kyoto Protocol.<br><br>The primary source of tetrafluoromethane in the environment is from the production of aluminium by electrolysis of alumina. Aluminium producers are taking effective steps in reducing emissions by better controlling the electrolysis process. Other sources include semiconductor manufacture and leakage from some refrigeration equipment. There are no natural sources of PFCs. |
| Sulphur Hexafluoride (SF6) | Sulfur hexafluoride (SF6) is an inorganic, colorless, odorless, non-toxic and non-flammable gas. | × | Another effect is the gas's ability to alter vocal sound waves. The gas can be inhaled in a small, safe amount and cause the breather's voice to sound very deep.<br><br>It is possible to safely breathe heavy gases such as xenon or sulfur hexafluoride as long as they include a 20% mixture of oxygen. | According to the Intergovernmental Panel on Climate Change, SF6 is the most potent greenhouse gas that it has evaluated, with a global warming potential of 22,800[4] times that of CO2.<br><br>Sulfur hexafluoride is also extremely long-lived, it is inert in the troposphere and stratosphere and has an estimated atmospheric lifetime of 800–3200 years<br><br>Average global SF6 concentrations increased by about seven percent per year during the 1980s and 1990s, mostly as the result of its use in the magnesium production industry, and by electrical utilities and electronics manufacturers. Given the low amounts of SF6 released compared to carbon dioxide, its overall contribution to global warming is estimated to be less than 0.2 percent.[citation needed]<br><br>In Europe, SF6 falls under the F-Gas directive which ban or control its usage for several applications. Since 1 January 2006, SF6 is banned as a tracer gas and in all applications except high-voltage switchgear |
| Volatile Organic Compounds (VOCs) | Organic chemical Compounds which have significant vapor pressures and which can affect the environment and human health. | × | Although VOCs include both man-made and naturally occurring chemical compounds, it is the anthropogenic VOCs that are regulated, especially for indoors where concentrations can be highest. VOCs are typically not acutely toxic but have chronic effects. Because the concentrations are usually low and the symptoms slow to develop, analysis of VOCs and their effects is a demanding area.<br><br>Respiratory, allergic, or immune effects in infants or children are associated with man-made VOCs and other indoor or outdoor air pollutants.[23]<br><br>Some VOCs, such as styrene and limonene, can react with nitrogen oxides or with ozone to produce new oxidation products and secondary aerosols, which can cause sensory irritation | The majority of VOCs arise from plants. An estimated 1150 Tg C/yr (Tg = 1012 grams) are produced annually by plants, the main constituent being isoprene.<br><br>Anthropogenic (human produced) emissions are about 10% of the biological level.<br><br>A major source of man-made VOCs are solvents, especially paints and protective coatings.<br><br>Chlorofluorocarbons and chlorocarbonsChlorofluorocarbons, which are banned or highly regulated, were widely used cleaning products and refrigerants. Tetrachloroethene is used widely in dry cleaning and by industry. Industrial use of fossil fuels produces VOCs either directly as products (e.g. gasoline) or indirectly as byproducts (e.g. automobile exhaust). |

| Pollutant | Info | Government Air Quality Indicator? | Health Impacts | Source |
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| | | | symptoms.[24][25] Unspecified VOCs are important in the creation of smog.[26]<br><br>Health effects include:<br><br>Eye, nose, and throat irritation; headaches, loss of coordination, nausea; damage to liver, kidney, and central nervous system. Some organics can cause cancer in animals; some are suspected or known to cause cancer in humans. Key signs or symptoms associated with exposure to VOCs include conjunctival irritation, nose and throat discomfort, headache, allergic skin reaction, dyspnea, declines in serum cholinesterase levels, nausea, emesis, epistaxis, fatigue, dizziness. The ability of organic chemicals to cause health effects varies greatly from those that are highly toxic, to those with no known health effect. As with other pollutants, the extent and nature of the health effect will depend on many factors including level of exposure and length of time exposed. Eye and respiratory tract irritation, headaches, dizziness, visual disorders, and memory impairment are among the immediate symptoms that some people have experienced soon after exposure to some organics. At present, not much is known about what health effects occur from the levels of organics usually found in homes. Many organic compounds are known to cause cancer in animals; some are suspected of causing, or are known to cause, cancer in humans. | |

## 9.2 Appendix B

## B1. Durham Paramics Flow Calibration Tables

Table AM Calibration Flow

| Traffic Flow | 08:00-09:00 - Turning Flows (vph) | | | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Random Seed 1 | Difference to Average | Random Seed 2 | Difference to Average | Random Seed 3 | Difference to Average | Random Seed 4 | Difference to Average | Random Seed 5 | Difference to Average | Random Seed 6 | Difference to Average | Random Seed 7 | Difference to Average | Random Seed 8 | Difference to Average | Random Seed 9 | Difference to Average | Random Seed 10 | Difference to Average | Average of 10 Runs |
| North Road (East) | 142 | 3 | 137 | 8 | 149 | 4 | 142 | 3 | 149 | 4 | 144 | 1 | 147 | 2 | 150 | 5 | 141 | 4 | 146 | 1 | 145 |
| Church Street (South) | 305 | 8 | 308 | 5 | 307 | 6 | 318 | 6 | 319 | 7 | 323 | 11 | 311 | 2 | 309 | 4 | 317 | 5 | 308 | 5 | 313 |
| Hallgarth Street (South) | 300 | 2 | 299 | 3 | 293 | 9 | 297 | 5 | 308 | 6 | 306 | 4 | 315 | 13 | 298 | 4 | 311 | 9 | 296 | 6 | 302 |
| New Elvet (North) | 589 | 10 | 604 | 5 | 599 | 0 | 604 | 5 | 596 | 3 | 598 | 1 | 619 | 20 | 599 | 0 | 585 | 14 | 596 | 3 | 599 |
| Hallgarth Street (North) | 200 | 3 | 200 | 3 | 189 | 8 | 198 | 1 | 194 | 3 | 203 | 6 | 194 | 3 | 196 | 1 | 207 | 10 | 193 | 4 | 197 |
| Sunderland Road (East) | 337 | 9 | 354 | 8 | 333 | 13 | 344 | 2 | 353 | 7 | 347 | 1 | 340 | 6 | 353 | 7 | 355 | 9 | 344 | 2 | 346 |
| New Elvet (South) | 681 | 25 | 658 | 2 | 654 | 3 | 657 | 1 | 645 | 12 | 653 | 4 | 640 | 17 | 646 | 11 | 670 | 14 | 661 | 5 | 657 |
| Margery (South) | 273 | 11 | 276 | 8 | 288 | 4 | 285 | 1 | 303 | 19 | 272 | 12 | 292 | 8 | 285 | 1 | 285 | 1 | 283 | 1 | 284 |
| Gilesgate (East) | 595 | 11 | 607 | 1 | 595 | 11 | 611 | 5 | 591 | 15 | 622 | 16 | 618 | 12 | 624 | 18 | 605 | 1 | 591 | 15 | 606 |
| Sunderland Road (West) | 269 | 1 | 261 | 9 | 271 | 1 | 277 | 7 | 271 | 1 | 273 | 3 | 268 | 2 | 268 | 2 | 270 | 0 | 276 | 6 | 270 |
| A690 Nevilles Cross Bank (North) | 636 | 3 | 631 | 8 | 634 | 5 | 652 | 14 | 635 | 4 | 630 | 9 | 640 | 2 | 631 | 8 | 656 | 18 | 640 | 2 | 639 |
| Claypath (West) | 195 | 1 | 191 | 3 | 190 | 4 | 194 | 0 | 198 | 4 | 198 | 4 | 195 | 1 | 191 | 3 | 194 | 0 | 194 | 0 | 194 |
| Claypath (East) | 250 | 18 | 266 | 2 | 280 | 12 | 267 | 1 | 261 | 7 | 277 | 9 | 269 | 1 | 268 | 0 | 279 | 11 | 262 | 6 | 268 |
| Church St Durham City (South) | 292 | 8 | 285 | 1 | 271 | 13 | 284 | 0 | 292 | 8 | 286 | 2 | 286 | 2 | 285 | 1 | 275 | 9 | 284 | 0 | 284 |
| Alexandria Crescent (South) | 488 | 9 | 493 | 4 | 495 | 2 | 503 | 6 | 496 | 1 | 493 | 4 | 497 | 0 | 501 | 4 | 502 | 5 | 500 | 3 | 497 |
| A181 Gilesgate (West) | 318 | 2 | 315 | 2 | 318 | 2 | 326 | 10 | 315 | 2 | 314 | 3 | 318 | 2 | 307 | 10 | 320 | 4 | 314 | 3 | 317 |
| A167 Pot and Glass Durham | 292 | 1 | 297 | 4 | 299 | 6 | 288 | 5 | 295 | 2 | 294 | 1 | 290 | 3 | 288 | 5 | 295 | 2 | 293 | 0 | 293 |
| A690 Crossgate Peth (West) | 318 | 1 | 314 | 3 | 318 | 1 | 315 | 2 | 317 | 0 | 316 | 1 | 321 | 4 | 316 | 1 | 313 | 4 | 318 | 1 | 317 |

| | 08:00-09:00 | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
| Aggregated Difference to Ave (vph) | 124 | 77 | 103 | 71 | 103 | 88 | 100 | 84 | 117 | 62 |
| Aggregated Difference to Ave (%) | 1.90% | 1.17% | 1.57% | 1.09% | 1.57% | 1.35% | 1.53% | 1.29% | 1.79% | 0.95% |

Table PM Calibration Flow

| Traffic Flow | 08:00-09:00 - Turning Flows (vph) | | | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Random Seed 1 | Difference to Average | Random Seed 2 | Difference to Average | Random Seed 3 | Difference to Average | Random Seed 4 | Difference to Average | Random Seed 5 | Difference to Average | Random Seed 6 | Difference to Average | Random Seed 7 | Difference to Average | Random Seed 8 | Difference to Average | Random Seed 9 | Difference to Average | Random Seed 10 | Difference to Average | Average of 10 Runs |
| North Road (East) | 122 | 5 | 116 | 2 | 119 | 2 | 124 | 7 | 106 | 12 | 119 | 2 | 118 | 1 | 114 | 4 | 120 | 3 | 117 | 1 | 118 |
| Church Street (South) | 283 | 7 | 265 | 11 | 283 | 7 | 272 | 4 | 269 | 7 | 274 | 2 | 273 | 3 | 286 | 10 | 278 | 2 | 276 | 0 | 276 |
| Hallgarth Street (South) | 273 | 2 | 280 | 9 | 256 | 15 | 272 | 1 | 278 | 7 | 280 | 9 | 263 | 8 | 266 | 5 | 272 | 1 | 269 | 2 | 271 |
| New Elvet (North) | 640 | 9 | 646 | 15 | 626 | 5 | 628 | 3 | 630 | 1 | 632 | 1 | 626 | 5 | 618 | 13 | 628 | 3 | 636 | 5 | 631 |
| Hallgarth Street (North) | 200 | 3 | 200 | 3 | 189 | 8 | 198 | 1 | 194 | 3 | 203 | 6 | 194 | 3 | 196 | 1 | 207 | 10 | 193 | 4 | 197 |
| Sunderland Road (East) | 337 | 9 | 354 | 8 | 333 | 13 | 344 | 2 | 353 | 7 | 347 | 1 | 340 | 6 | 353 | 7 | 355 | 9 | 344 | 2 | 346 |
| New Elvet (South) | 610 | 15 | 636 | 11 | 623 | 2 | 637 | 12 | 628 | 3 | 624 | 1 | 635 | 10 | 605 | 20 | 636 | 11 | 620 | 5 | 625 |
| Margery (South) | 232 | 0 | 238 | 6 | 231 | 1 | 234 | 2 | 234 | 2 | 233 | 1 | 226 | 6 | 221 | 11 | 233 | 1 | 238 | 6 | 232 |
| Gilesgate (East) | 533 | 3 | 563 | 27 | 539 | 3 | 536 | 0 | 526 | 10 | 531 | 5 | 531 | 5 | 521 | 15 | 536 | 0 | 540 | 4 | 536 |
| Sunderland Road (West) | 201 | 0 | 207 | 6 | 187 | 14 | 195 | 6 | 207 | 6 | 194 | 7 | 205 | 4 | 200 | 1 | 206 | 5 | 211 | 10 | 201 |
| A690 Nevilles Cross Bank (North) | 648 | 2 | 648 | 2 | 645 | 5 | 661 | 11 | 652 | 2 | 647 | 3 | 657 | 7 | 666 | 16 | 653 | 3 | 622 | 28 | 650 |
| Claypath (West) | 176 | 6 | 190 | 8 | 175 | 7 | 183 | 1 | 181 | 1 | 181 | 1 | 183 | 1 | 182 | 0 | 183 | 1 | 186 | 4 | 182 |
| Claypath (East) | 621 | 8 | 601 | 12 | 603 | 10 | 607 | 6 | 631 | 18 | 605 | 8 | 615 | 2 | 609 | 4 | 623 | 10 | 614 | 1 | 613 |
| Church St Durham City (South) | 343 | 3 | 324 | 16 | 329 | 11 | 339 | 1 | 343 | 3 | 347 | 7 | 342 | 2 | 345 | 5 | 342 | 2 | 347 | 7 | 340 |
| Alexandria Crescent (South) | 573 | 5 | 560 | 8 | 578 | 10 | 558 | 10 | 560 | 8 | 573 | 5 | 587 | 19 | 557 | 11 | 580 | 12 | 557 | 11 | 568 |
| A181 Gilesgate (West) | 391 | 4 | 398 | 11 | 379 | 8 | 393 | 6 | 393 | 6 | 378 | 9 | 373 | 14 | 397 | 10 | 378 | 9 | 394 | 7 | 387 |
| A167 Pot and Glass Durham | 354 | 6 | 370 | 10 | 361 | 1 | 364 | 4 | 363 | 3 | 360 | 0 | 351 | 9 | 361 | 1 | 349 | 11 | 369 | 9 | 360 |
| A690 Crossgate Peth (West) | 447 | 2 | 471 | 22 | 432 | 17 | 473 | 24 | 451 | 2 | 444 | 5 | 440 | 9 | 439 | 10 | 438 | 11 | 458 | 9 | 449 |

| | 08:00-09:00 | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
| Aggregated Difference to Ave (vph) | 88 | 185 | 140 | 100 | 99 | 73 | 113 | 144 | 104 | 115 |
| Aggregated Difference to Ave (%) | 1.26% | 2.65% | 2.01% | 1.43% | 1.42% | 1.04% | 1.62% | 2.06% | 1.49% | 1.64% |

## B2. Durham Paramics Flow Validation Tables

### Table AM Peak Link Flows

| | Link Description | Matrix Flow | Modelled Flow | Difference | Requirement (based on flows) | Is this criteria fulfilled? | GEH Statistic |
|---|---|---|---|---|---|---|---|
| 1 | Millburngate Bridge EB | 2112 | 1901 | -211 | Flow within 15% | Yes | 4.7 |
| 2 | Millburngate Bridge WB | 1741 | 1653 | -88 | Flow within 15% | Yes | 2.1 |
| 3 | Hallgarth Street NB | 352 | 323 | -29 | Flow within 100vph | Yes | 1.6 |
| 4 | Hallgarth Street SB | 420 | 411 | -9 | Flow within 100vph | Yes | 0.4 |
| 5 | Gilesgate WB | 725 | 722 | -3 | Flow within 15% | Yes | 0.1 |
| 6 | Gilesgate EB | 780 | 728 | -52 | Flow within 15% | Yes | 1.9 |
| 7 | Framwellgate NB | 1117 | 1049 | -68 | Flow within 15% | Yes | 2.1 |
| 8 | Framwellgate SB | 1448 | 1458 | 10 | Flow within 15% | Yes | 0.3 |
| 9 | St Godric's Road WB | 592 | 571 | -21 | Flow within 100vph | Yes | 0.9 |
| 10 | St Godric's Road EB | 756 | 744 | -12 | Flow within 15% | Yes | 0.4 |
| 11 | Sherburn Road EB | 623 | 649 | 26 | Flow within 100vph | Yes | 1.0 |
| 12 | Sherburn Road WB | 562 | 534 | -28 | Flow within 100vph | Yes | 1.2 |
| 13 | New Elvet | 783 | 764 | -19 | Flow within 15% | Yes | 0.7 |
| 14 | Leazes Road EB | 1569 | 1639 | 70 | Flow within 15% | Yes | 1.7 |
| 15 | Leazes Road WB | 1563 | 1670 | 107 | Flow within 15% | Yes | 2.7 |
| 16 | A690 NB | 941 | 952 | 11 | Flow within 15% | Yes | 0.4 |
| 17 | A690 SB | 1142 | 1043 | -99 | Flow within 15% | Yes | 3.0 |
| 18 | Crossgate Peth WB | 485 | 500 | 15 | Flow within 100vph | Yes | 0.7 |
| 19 | Crossgate Peth EB | 1102 | 1068 | -34 | Flow within 15% | Yes | 1.0 |
| 20 | Sunderland Road EB | 312 | 287 | -25 | Flow within 100vph | Yes | 1.4 |
| 21 | Sunderland Road WB | 289 | 333 | 44 | Flow within 100vph | Yes | 2.5 |
| 22 | Milburngate NB | 178 | 203 | 25 | Flow within 100vph | Yes | 1.8 |
| 23 | Church Street NB | 658 | 624 | -34 | Flow within 100vph | Yes | 1.3 |
| 24 | Church Street SB | 459 | 444 | -15 | Flow within 100vph | Yes | 0.7 |
| 25 | Claypath EB | 217 | 169 | -48 | Flow within 100vph | Yes | 3.5 |
| 26 | Claypath WB | 80 | 75 | -5 | Flow within 100vph | Yes | 0.6 |

### Table PM Peak Link Flows

| | Link Description | Matrix Flow | Modelled Flow | Difference | Requirement (based on flows) | Is this criteria fulfilled? | GEH Statistic |
|---|---|---|---|---|---|---|---|
| 1 | Millburngate Bridge EB | 1725 | 1640 | -85 | Flow within 15% | Yes | 2.1 |
| 2 | Millburngate Bridge WB | 2312 | 2286 | -26 | Flow within 15% | Yes | 0.5 |
| 3 | Hallgarth Street NB | 265 | 278 | 13 | Flow within 100vph | Yes | 0.8 |
| 4 | Hallgarth Street SB | 402 | 348 | -54 | Flow within 100vph | Yes | 2.8 |
| 5 | Gilesgate WB | 541 | 524 | -17 | Flow within 100vph | Yes | 0.7 |
| 6 | Gilesgate EB | 513 | 546 | 33 | Flow within 100vph | Yes | 1.4 |
| 7 | Framwellgate NB | 1204 | 1153 | -51 | Flow within 15% | Yes | 1.5 |
| 8 | Framwellgate SB | 1153 | 1123 | -30 | Flow within 15% | Yes | 0.9 |
| 9 | St Godric's Road WB | 756 | 752 | -4 | Flow within 15% | Yes | 0.1 |
| 10 | St Godric's Road EB | 540 | 545 | 5 | Flow within 100vph | Yes | 0.2 |
| 11 | Sherburn Road EB | 612 | 544 | -68 | Flow within 100vph | Yes | 2.8 |
| 12 | Sherburn Road WB | 625 | 623 | -2 | Flow within 100vph | Yes | 0.1 |
| 13 | New Elvet | 714 | 675 | -39 | Flow within 15% | Yes | 1.5 |
| 14 | Leazes Road EB | 1802 | 1725 | -77 | Flow within 15% | Yes | 1.8 |
| 15 | Leazes Road WB | 1745 | 1689 | -56 | Flow within 15% | Yes | 1.4 |
| 16 | A690 NB | 1295 | 1379 | 84 | Flow within 15% | Yes | 2.3 |
| 17 | A690 SB | 1245 | 1193 | -52 | Flow within 15% | Yes | 1.5 |
| 18 | Crossgate Peth WB | 732 | 678 | -54 | Flow within 15% | Yes | 2.0 |
| 19 | Crossgate Peth EB | 682 | 692 | 10 | Flow within 100vph | Yes | 0.4 |
| 20 | Sunderland Road EB | 142 | 150 | 8 | Flow within 100vph | Yes | 0.7 |
| 21 | Sunderland Road WB | 145 | 133 | -12 | Flow within 100vph | Yes | 1.0 |
| 22 | Milburngate NB | 192 | 189 | -3 | Flow within 100vph | Yes | 0.2 |
| 23 | Church Street NB | 421 | 387 | -34 | Flow within 100vph | Yes | 1.7 |
| 24 | Church Street SB | 435 | 462 | 27 | Flow within 100vph | Yes | 1.3 |
| 25 | Claypath EB | 265 | 271 | 6 | Flow within 100vph | Yes | 0.4 |
| 26 | Claypath WB | 95 | 82 | -13 | Flow within 100vph | Yes | 1.4 |

## Table 24 hour Link Flows

| | Site | Direction | Time | Flow (Veh) Traffic Count | Paramics Model | Difference | Is this criteria fulfilled? | GEH |
|---|---|---|---|---|---|---|---|---|
| 1 | 9994 | South | 00:00 | 28 | 2 | -26 | Yes | 6.7 |
| | Dragon Lane | | 01:00 | 16 | 3 | -13 | Yes | 4.1 |
| | | | 02:00 | 8 | 2 | -6 | Yes | 2.7 |
| | | | 03:00 | 18 | 8 | -10 | Yes | 2.8 |
| | | | 04:00 | 19 | 5 | -14 | Yes | 4.0 |
| | | | 05:00 | 62 | 33 | -29 | Yes | 4.2 |
| | | | 06:00 | 135 | 191 | 56 | Yes | 4.4 |
| | | | 07:00 | 271 | 363 | 92 | Yes | 5.2 |
| | | | 08:00 | 414 | 365 | -49 | Yes | 2.5 |
| | | | 09:00 | 224 | 292 | 68 | Yes | 4.2 |
| | | | 10:00 | 267 | 251 | -16 | Yes | 1.0 |
| | | | 11:00 | 273 | 228 | -45 | Yes | 2.8 |
| | | | 12:00 | 314 | 274 | -40 | Yes | 2.3 |
| | | | 13:00 | 340 | 275 | -65 | Yes | 3.7 |
| | | | 14:00 | 350 | 281 | -69 | Yes | 3.9 |
| | | | 15:00 | 365 | 322 | -43 | Yes | 2.3 |
| | | | 16:00 | 356 | 387 | 31 | Yes | 1.6 |
| | | | 17:00 | 389 | 285 | -104 | No | 5.7 |
| | | | 18:00 | 427 | 259 | -168 | No | 9.1 |
| | | | 19:00 | 342 | 210 | -132 | No | 7.9 |
| | | | 20:00 | 274 | 135 | -139 | No | 9.7 |
| | | | 21:00 | 222 | 85 | -137 | No | 11.1 |
| | | | 22:00 | 141 | 50 | -91 | Yes | 9.3 |
| | | | 23:00 | 40 | 16 | -24 | Yes | 4.5 |
| 2 | 9994 | North | 00:00 | 14 | 9 | -5 | Yes | 1.5 |
| | Dragon Lane | | 01:00 | 13 | 6 | -7 | Yes | 2.4 |
| | | | 02:00 | 11 | 4 | -7 | Yes | 2.5 |
| | | | 03:00 | 10 | 2 | -8 | Yes | 3.4 |
| | | | 04:00 | 22 | 8 | -14 | Yes | 3.7 |
| | | | 05:00 | 66 | 15 | -51 | Yes | 8.0 |
| | | | 06:00 | 140 | 130 | -10 | Yes | 0.9 |
| | | | 07:00 | 323 | 266 | -57 | Yes | 3.3 |
| | | | 08:00 | 219 | 265 | 46 | Yes | 3.0 |
| | | | 09:00 | 212 | 127 | -85 | Yes | 6.5 |
| | | | 10:00 | 263 | 124 | -139 | No | 10.0 |
| | | | 11:00 | 278 | 135 | -143 | No | 10.0 |
| | | | 12:00 | 244 | 134 | -110 | No | 8.0 |
| | | | 13:00 | 275 | 147 | -128 | No | 8.8 |
| | | | 14:00 | 263 | 185 | -78 | Yes | 5.2 |
| | | | 15:00 | 307 | 228 | -79 | Yes | 4.8 |
| | | | 16:00 | 342 | 259 | -83 | Yes | 4.8 |
| | | | 17:00 | 379 | 259 | -120 | No | 6.7 |
| | | | 18:00 | 274 | 155 | -119 | No | 8.1 |
| | | | 19:00 | 219 | 102 | -117 | No | 9.2 |
| | | | 20:00 | 189 | 88 | -101 | No | 8.6 |
| | | | 21:00 | 152 | 56 | -96 | Yes | 9.4 |
| | | | 22:00 | 96 | 40 | -56 | Yes | 6.8 |
| | | | 23:00 | 38 | 9 | -29 | Yes | 6.0 |
| 3 | 2185 | East | 00:00 | 36 | 14 | -22 | Yes | 4.5 |
| | A181 Dragonville | | 01:00 | 14 | 11 | -3 | Yes | 0.9 |
| | | | 02:00 | 15 | 6 | -9 | Yes | 2.8 |
| | | | 03:00 | 7 | 11 | 4 | Yes | 1.3 |
| | | | 04:00 | 14 | 17 | 3 | Yes | 0.8 |
| | | | 05:00 | 62 | 58 | -4 | Yes | 0.5 |
| | | | 06:00 | 150 | 375 | 225 | No | 13.9 |
| | | | 07:00 | 429 | 664 | 235 | No | 10.1 |
| | | | 08:00 | 475 | 665 | 190 | No | 8.0 |
| | | | 09:00 | 413 | 628 | 215 | No | 9.4 |
| | | | 10:00 | 428 | 527 | 99 | Yes | 4.5 |
| | | | 11:00 | 498 | 507 | 9 | Yes | 0.4 |
| | | | 12:00 | 513 | 548 | 35 | Yes | 1.5 |
| | | | 13:00 | 492 | 574 | 82 | Yes | 3.5 |
| | | | 14:00 | 612 | 545 | -67 | Yes | 2.8 |
| | | | 15:00 | 685 | 598 | -87 | Yes | 3.4 |
| | | | 16:00 | 786 | 658 | -128 | No | 4.8 |
| | | | 17:00 | 773 | 569 | -204 | No | 7.9 |
| | | | 18:00 | 539 | 519 | -20 | Yes | 0.9 |
| | | | 19:00 | 430 | 444 | 14 | Yes | 0.7 |
| | | | 20:00 | 289 | 313 | 24 | Yes | 1.4 |
| | | | 21:00 | 208 | 207 | -1 | Yes | 0.1 |
| | | | 22:00 | 127 | 125 | -2 | Yes | 0.1 |
| | | | 23:00 | 68 | 46 | -22 | Yes | 3.0 |
| 4 | 2185 | West | 00:00 | 26 | 24 | -2 | Yes | 0.5 |
| | A181 Dragonville | | 01:00 | 7 | 12 | 5 | Yes | 1.7 |
| | | | 02:00 | 11 | 11 | 0 | Yes | 0.1 |
| | | | 03:00 | 13 | 8 | -5 | Yes | 1.5 |
| | | | 04:00 | 21 | 17 | -4 | Yes | 0.8 |
| | | | 05:00 | 85 | 42 | -43 | Yes | 5.4 |
| | | | 06:00 | 192 | 313 | 121 | No | 7.6 |
| | | | 07:00 | 535 | 646 | 111 | No | 4.6 |
| | | | 08:00 | 617 | 531 | -86 | Yes | 3.6 |
| | | | 09:00 | 539 | 293 | -246 | No | 12.1 |
| | | | 10:00 | 479 | 314 | -165 | No | 8.3 |
| | | | 11:00 | 470 | 336 | -134 | No | 6.7 |
| | | | 12:00 | 469 | 350 | -119 | No | 5.9 |
| | | | 13:00 | 483 | 364 | -119 | No | 5.8 |
| | | | 14:00 | 474 | 407 | -67 | Yes | 3.2 |
| | | | 15:00 | 480 | 477 | -3 | Yes | 0.1 |
| | | | 16:00 | 530 | 471 | -59 | Yes | 2.6 |
| | | | 17:00 | 507 | 382 | -125 | No | 5.9 |
| | | | 18:00 | 496 | 326 | -170 | No | 8.4 |
| | | | 19:00 | 319 | 264 | -55 | Yes | 3.2 |
| | | | 20:00 | 186 | 215 | 29 | Yes | 2.1 |
| | | | 21:00 | 126 | 144 | 18 | Yes | 1.5 |
| | | | 22:00 | 84 | 105 | 21 | Yes | 2.2 |
| | | | 23:00 | 51 | 22 | -29 | Yes | 4.8 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| 5 | **2505** | **East** | 00:00 | 19 | 9 | -10 | Yes | 2.7 |
| | **Sunderland Road** | | 01:00 | 11 | 3 | -8 | Yes | 3.1 |
| | | | 02:00 | 6 | 1 | -5 | Yes | 2.8 |
| | | | 03:00 | 11 | 3 | -8 | Yes | 3.0 |
| | | | 04:00 | 16 | 6 | -10 | Yes | 2.9 |
| | | | 05:00 | 72 | 19 | -53 | Yes | 7.8 |
| | | | 06:00 | 101 | 100 | -1 | Yes | 0.1 |
| | | | 07:00 | 249 | 243 | -6 | Yes | 0.4 |
| | | | 08:00 | 337 | 240 | -97 | Yes | 5.7 |
| | | | 09:00 | 321 | 251 | -70 | Yes | 4.2 |
| | | | 10:00 | 343 | 252 | -91 | Yes | 5.3 |
| | | | 11:00 | 348 | 250 | -98 | Yes | 5.7 |
| | | | 12:00 | 353 | 270 | -83 | Yes | 4.7 |
| | | | 13:00 | 362 | 237 | -125 | No | 7.2 |
| | | | 14:00 | 328 | 186 | -142 | No | 8.8 |
| | | | 15:00 | 381 | 110 | -271 | No | 17.3 |
| | | | 16:00 | 361 | 182 | -179 | No | 10.8 |
| | | | 17:00 | 326 | 150 | -176 | No | 11.4 |
| | | | 18:00 | 311 | 153 | -158 | No | 10.4 |
| | | | 19:00 | 221 | 255 | 34 | Yes | 2.2 |
| | | | 20:00 | 148 | 159 | 11 | Yes | 0.9 |
| | | | 21:00 | 134 | 110 | -24 | Yes | 2.2 |
| | | | 22:00 | 69 | 64 | -5 | Yes | 0.6 |
| | | | 23:00 | 35 | 20 | -15 | Yes | 2.9 |
| 6 | **2505** | **West** | 00:00 | 21 | 3 | -18 | Yes | 5.1 |
| | **Sunderland Road** | | 01:00 | 9 | 4 | -5 | Yes | 2.0 |
| | | | 02:00 | 9 | 0 | -9 | Yes | 4.2 |
| | | | 03:00 | 6 | 3 | -3 | Yes | 1.5 |
| | | | 04:00 | 9 | 3 | -6 | Yes | 2.3 |
| | | | 05:00 | 23 | 14 | -9 | Yes | 2.0 |
| | | | 06:00 | 71 | 56 | -15 | Yes | 1.9 |
| | | | 07:00 | 178 | 249 | 71 | Yes | 4.8 |
| | | | 08:00 | 289 | 244 | -45 | Yes | 2.7 |
| | | | 09:00 | 301 | 168 | -133 | No | 8.7 |
| | | | 10:00 | 353 | 129 | -224 | No | 14.4 |
| | | | 11:00 | 400 | 113 | -287 | No | 17.9 |
| | | | 12:00 | 425 | 128 | -297 | No | 17.9 |
| | | | 13:00 | 415 | 128 | -287 | No | 17.4 |
| | | | 14:00 | 421 | 140 | -281 | No | 16.8 |
| | | | 15:00 | 410 | 134 | -276 | No | 16.7 |
| | | | 16:00 | 376 | 186 | -190 | No | 11.4 |
| | | | 17:00 | 407 | 133 | -274 | No | 16.7 |
| | | | 18:00 | 422 | 122 | -300 | No | 18.2 |
| | | | 19:00 | 332 | 113 | -219 | No | 14.7 |
| | | | 20:00 | 190 | 67 | -123 | No | 10.8 |
| | | | 21:00 | 120 | 42 | -78 | Yes | 8.7 |
| | | | 22:00 | 108 | 27 | -81 | Yes | 9.9 |
| | | | 23:00 | 40 | 8 | -32 | Yes | 6.6 |
| 7 | **1078** | **South** | 00:00 | 18 | 7 | -11 | Yes | 3.1 |
| | **Hallgarth Street** | | 01:00 | 7 | 5 | -2 | Yes | 0.8 |
| | | | 02:00 | 5 | 6 | 1 | Yes | 0.4 |
| | | | 03:00 | 2 | 9 | 7 | Yes | 2.8 |
| | | | 04:00 | 8 | 9 | 1 | Yes | 0.3 |
| | | | 05:00 | 27 | 41 | 14 | Yes | 2.3 |
| | | | 06:00 | 107 | 140 | 33 | Yes | 2.9 |
| | | | 07:00 | 276 | 335 | 59 | Yes | 3.4 |
| | | | 08:00 | 368 | 491 | 123 | No | 6.0 |
| | | | 09:00 | 245 | 311 | 66 | Yes | 3.9 |
| | | | 10:00 | 196 | 245 | 49 | Yes | 3.3 |
| | | | 11:00 | 209 | 222 | 13 | Yes | 0.9 |
| | | | 12:00 | 238 | 247 | 9 | Yes | 0.6 |
| | | | 13:00 | 223 | 269 | 46 | Yes | 3.0 |
| | | | 14:00 | 224 | 307 | 83 | Yes | 5.1 |
| | | | 15:00 | 264 | 394 | 130 | No | 7.1 |
| | | | 16:00 | 328 | 363 | 35 | Yes | 1.9 |
| | | | 17:00 | 296 | 348 | 52 | Yes | 2.9 |
| | | | 18:00 | 240 | 293 | 53 | Yes | 3.3 |
| | | | 19:00 | 176 | 297 | 121 | No | 7.8 |
| | | | 20:00 | 113 | 181 | 68 | Yes | 5.6 |
| | | | 21:00 | 98 | 118 | 20 | Yes | 2.0 |
| | | | 22:00 | 53 | 85 | 32 | Yes | 3.9 |
| | | | 23:00 | 38 | 24 | -14 | Yes | 2.5 |
| 8 | **1078** | **North** | 00:00 | 10 | 2 | -8 | Yes | 3.3 |
| | **Hallgarth Street** | | 01:00 | 7 | 1 | -6 | Yes | 3.1 |
| | | | 02:00 | 5 | 4 | -1 | Yes | 0.3 |
| | | | 03:00 | 4 | 2 | -2 | Yes | 1.0 |
| | | | 04:00 | 5 | 7 | 2 | Yes | 1.0 |
| | | | 05:00 | 26 | 18 | -8 | Yes | 1.6 |
| | | | 06:00 | 98 | 164 | 66 | Yes | 5.8 |
| | | | 07:00 | 370 | 393 | 23 | Yes | 1.2 |
| | | | 08:00 | 346 | 263 | -83 | Yes | 4.7 |
| | | | 09:00 | 265 | 303 | 38 | Yes | 2.3 |
| | | | 10:00 | 207 | 256 | 49 | Yes | 3.2 |
| | | | 11:00 | 203 | 231 | 28 | Yes | 1.9 |
| | | | 12:00 | 223 | 243 | 20 | Yes | 1.3 |
| | | | 13:00 | 214 | 259 | 45 | Yes | 2.9 |
| | | | 14:00 | 210 | 255 | 45 | Yes | 3.0 |
| | | | 15:00 | 264 | 289 | 25 | Yes | 1.5 |
| | | | 16:00 | 349 | 232 | -117 | No | 6.8 |
| | | | 17:00 | 336 | 278 | -58 | Yes | 3.3 |
| | | | 18:00 | 252 | 229 | -23 | Yes | 1.5 |
| | | | 19:00 | 152 | 208 | 56 | Yes | 4.2 |
| | | | 20:00 | 129 | 145 | 16 | Yes | 1.4 |
| | | | 21:00 | 82 | 99 | 17 | Yes | 1.8 |
| | | | 22:00 | 52 | 69 | 17 | Yes | 2.2 |
| | | | 23:00 | 26 | 21 | -5 | Yes | 1.0 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| 9 | 2048 | East | 00:00 | 25 | 35 | 10 | Yes | 1.8 |
| | A690 Nevilles Cross Bank | | 01:00 | 13 | 18 | 5 | Yes | 1.2 |
| | | | 02:00 | 17 | 13 | -4 | Yes | 1.0 |
| | | | 03:00 | 12 | 13 | 1 | Yes | 0.4 |
| | | | 04:00 | 24 | 18 | -6 | Yes | 1.2 |
| | | | 05:00 | 140 | 50 | -90 | Yes | 9.2 |
| | | | 06:00 | 478 | 548 | 70 | Yes | 3.1 |
| | | | 07:00 | 993 | 990 | -3 | Yes | 0.1 |
| | | | 08:00 | 993 | 927 | -66 | Yes | 2.1 |
| | | | 09:00 | 718 | 789 | 71 | Yes | 2.6 |
| | | | 10:00 | 683 | 536 | -147 | No | 6.0 |
| | | | 11:00 | 673 | 531 | -142 | No | 5.8 |
| | | | 12:00 | 680 | 598 | -82 | Yes | 3.2 |
| | | | 13:00 | 606 | 600 | -6 | Yes | 0.2 |
| | | | 14:00 | 655 | 675 | 20 | Yes | 0.8 |
| | | | 15:00 | 702 | 756 | 54 | Yes | 2.0 |
| | | | 16:00 | 701 | 752 | 51 | Yes | 1.9 |
| | | | 17:00 | 701 | 773 | 72 | Yes | 2.7 |
| | | | 18:00 | 603 | 734 | 131 | No | 5.1 |
| | | | 19:00 | 411 | 441 | 30 | Yes | 1.5 |
| | | | 20:00 | 238 | 339 | 101 | No | 5.9 |
| | | | 21:00 | 193 | 250 | 57 | Yes | 3.9 |
| | | | 22:00 | 119 | 173 | 54 | Yes | 4.5 |
| | | | 23:00 | 78 | 50 | -28 | Yes | 3.5 |
| 10 | 2048 | West | 00:00 | 44 | 22 | -22 | Yes | 3.9 |
| | A690 Nevilles Cross Bank | | 01:00 | 29 | 16 | -13 | Yes | 2.7 |
| | | | 02:00 | 17 | 10 | -7 | Yes | 1.8 |
| | | | 03:00 | 17 | 17 | 0 | Yes | 0.0 |
| | | | 04:00 | 24 | 27 | 3 | Yes | 0.6 |
| | | | 05:00 | 62 | 81 | 19 | Yes | 2.2 |
| | | | 06:00 | 190 | 356 | 166 | No | 10.0 |
| | | | 07:00 | 610 | 657 | 47 | Yes | 1.9 |
| | | | 08:00 | 625 | 710 | 85 | Yes | 3.3 |
| | | | 09:00 | 641 | 688 | 47 | Yes | 1.8 |
| | | | 10:00 | 579 | 666 | 87 | Yes | 3.5 |
| | | | 11:00 | 643 | 656 | 13 | Yes | 0.5 |
| | | | 12:00 | 649 | 717 | 68 | Yes | 2.6 |
| | | | 13:00 | 642 | 723 | 81 | Yes | 3.1 |
| | | | 14:00 | 695 | 742 | 47 | Yes | 1.8 |
| | | | 15:00 | 763 | 780 | 17 | Yes | 0.6 |
| | | | 16:00 | 957 | 1045 | 88 | Yes | 2.8 |
| | | | 17:00 | 963 | 1082 | 119 | Yes | 3.7 |
| | | | 18:00 | 719 | 707 | -12 | Yes | 0.5 |
| | | | 19:00 | 554 | 533 | -21 | Yes | 0.9 |
| | | | 20:00 | 390 | 319 | -71 | Yes | 3.8 |
| | | | 21:00 | 292 | 246 | -46 | Yes | 2.8 |
| | | | 22:00 | 215 | 152 | -63 | Yes | 4.7 |
| | | | 23:00 | 133 | 50 | -83 | Yes | 8.6 |
| 11 | 2050 | South | 00:00 | 36 | 14 | -22 | Yes | 4.3 |
| | New Elvet | | 01:00 | 23 | 9 | -14 | Yes | 3.5 |
| | | | 02:00 | 21 | 10 | -11 | Yes | 2.8 |
| | | | 03:00 | 7 | 12 | 5 | Yes | 1.6 |
| | | | 04:00 | 16 | 17 | 1 | Yes | 0.3 |
| | | | 05:00 | 54 | 65 | 11 | Yes | 1.5 |
| | | | 06:00 | 230 | 294 | 64 | Yes | 4.0 |
| | | | 07:00 | 516 | 686 | 170 | No | 6.9 |
| | | | 08:00 | 639 | 769 | 130 | No | 4.9 |
| | | | 09:00 | 501 | 596 | 95 | Yes | 4.1 |
| | | | 10:00 | 405 | 442 | 37 | Yes | 1.8 |
| | | | 11:00 | 467 | 406 | -61 | Yes | 2.9 |
| | | | 12:00 | 496 | 478 | -18 | Yes | 0.8 |
| | | | 13:00 | 486 | 450 | -36 | Yes | 1.7 |
| | | | 14:00 | 510 | 578 | 68 | Yes | 2.9 |
| | | | 15:00 | 605 | 827 | 222 | No | 8.3 |
| | | | 16:00 | 662 | 759 | 97 | Yes | 3.7 |
| | | | 17:00 | 606 | 767 | 161 | No | 6.1 |
| | | | 18:00 | 487 | 585 | 98 | Yes | 4.2 |
| | | | 19:00 | 372 | 446 | 74 | Yes | 3.7 |
| | | | 20:00 | 266 | 325 | 59 | Yes | 3.4 |
| | | | 21:00 | 236 | 185 | -51 | Yes | 3.5 |
| | | | 22:00 | 135 | 136 | 1 | Yes | 0.1 |
| | | | 23:00 | 89 | 36 | -53 | Yes | 6.7 |
| 12 | 2050 | North | 00:00 | 33 | 13 | -20 | Yes | 4.2 |
| | New Elvet | | 01:00 | 19 | 7 | -12 | Yes | 3.3 |
| | | | 02:00 | 19 | 11 | -8 | Yes | 2.1 |
| | | | 03:00 | 8 | 8 | 0 | Yes | 0.0 |
| | | | 04:00 | 13 | 13 | 0 | Yes | 0.0 |
| | | | 05:00 | 56 | 42 | -14 | Yes | 2.0 |
| | | | 06:00 | 184 | 322 | 138 | No | 8.7 |
| | | | 07:00 | 547 | 817 | 270 | No | 10.3 |
| | | | 08:00 | 636 | 846 | 210 | No | 7.7 |
| | | | 09:00 | 494 | 743 | 249 | No | 10.0 |
| | | | 10:00 | 429 | 537 | 108 | No | 4.9 |
| | | | 11:00 | 426 | 509 | 83 | Yes | 3.8 |
| | | | 12:00 | 437 | 528 | 91 | Yes | 4.1 |
| | | | 13:00 | 464 | 534 | 70 | Yes | 3.1 |
| | | | 14:00 | 447 | 579 | 132 | No | 5.8 |
| | | | 15:00 | 543 | 650 | 107 | No | 4.4 |
| | | | 16:00 | 604 | 639 | 35 | Yes | 1.4 |
| | | | 17:00 | 596 | 670 | 74 | Yes | 3.0 |
| | | | 18:00 | 484 | 526 | 42 | Yes | 1.9 |
| | | | 19:00 | 306 | 455 | 149 | No | 7.6 |
| | | | 20:00 | 241 | 281 | 40 | Yes | 2.5 |
| | | | 21:00 | 193 | 214 | 21 | Yes | 1.5 |
| | | | 22:00 | 136 | 151 | 15 | Yes | 1.3 |
| | | | 23:00 | 77 | 48 | -29 | Yes | 3.7 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| 13 | 2138 | South | 00:00 | 34 | 30 | -4 | Yes | 0.6 |
| | A167 | | 01:00 | 23 | 22 | -1 | Yes | 0.2 |
| | | | 02:00 | 16 | 16 | 0 | Yes | 0.0 |
| | | | 03:00 | 14 | 22 | 8 | Yes | 2.0 |
| | | | 04:00 | 29 | 30 | 1 | Yes | 0.2 |
| | | | 05:00 | 103 | 109 | 6 | Yes | 0.6 |
| | | | 06:00 | 309 | 495 | 186 | No | 9.3 |
| | | | 07:00 | 813 | 959 | 146 | No | 4.9 |
| | | | 08:00 | 871 | 910 | 39 | Yes | 1.3 |
| | | | 09:00 | 739 | 853 | 114 | No | 4.0 |
| | | | 10:00 | 676 | 768 | 92 | Yes | 3.4 |
| | | | 11:00 | 704 | 752 | 48 | Yes | 1.8 |
| | | | 12:00 | 780 | 780 | 0 | Yes | 0.0 |
| | | | 13:00 | 785 | 807 | 22 | Yes | 0.8 |
| | | | 14:00 | 813 | 790 | -23 | Yes | 0.8 |
| | | | 15:00 | 921 | 865 | -56 | Yes | 1.9 |
| | | | 16:00 | 955 | 906 | -49 | Yes | 1.6 |
| | | | 17:00 | 945 | 770 | -175 | No | 6.0 |
| | | | 18:00 | 766 | 696 | -70 | Yes | 2.6 |
| | | | 19:00 | 577 | 756 | 179 | No | 6.9 |
| | | | 20:00 | 392 | 514 | 122 | No | 5.7 |
| | | | 21:00 | 269 | 334 | 65 | Yes | 3.7 |
| | | | 22:00 | 180 | 220 | 40 | Yes | 2.8 |
| | | | 23:00 | 103 | 76 | -27 | Yes | 2.9 |
| 14 | 2138 | North | 00:00 | 45 | 24 | -21 | Yes | 3.6 |
| | A167 | | 01:00 | 21 | 16 | -5 | Yes | 1.2 |
| | | | 02:00 | 25 | 15 | -10 | Yes | 2.2 |
| | | | 03:00 | 19 | 14 | -5 | Yes | 1.2 |
| | | | 04:00 | 23 | 20 | -3 | Yes | 0.6 |
| | | | 05:00 | 104 | 55 | -49 | Yes | 5.5 |
| | | | 06:00 | 452 | 432 | -20 | Yes | 1.0 |
| | | | 07:00 | 902 | 857 | -45 | Yes | 1.5 |
| | | | 08:00 | 828 | 832 | 4 | Yes | 0.2 |
| | | | 09:00 | 826 | 700 | -126 | No | 4.5 |
| | | | 10:00 | 750 | 542 | -208 | No | 8.2 |
| | | | 11:00 | 757 | 560 | -197 | No | 7.7 |
| | | | 12:00 | 775 | 581 | -194 | No | 7.4 |
| | | | 13:00 | 784 | 574 | -210 | No | 8.1 |
| | | | 14:00 | 802 | 655 | -147 | No | 5.4 |
| | | | 15:00 | 829 | 766 | -63 | Yes | 2.2 |
| | | | 16:00 | 841 | 838 | -3 | Yes | 0.1 |
| | | | 17:00 | 858 | 838 | -20 | Yes | 0.7 |
| | | | 18:00 | 744 | 681 | -63 | Yes | 2.4 |
| | | | 19:00 | 461 | 481 | 20 | Yes | 0.9 |
| | | | 20:00 | 303 | 330 | 27 | Yes | 1.5 |
| | | | 21:00 | 266 | 236 | -30 | Yes | 1.9 |
| | | | 22:00 | 172 | 160 | -12 | Yes | 0.9 |
| | | | 23:00 | 91 | 51 | -40 | Yes | 4.8 |
| 15 | 2382 | East | 00:00 | 58 | 23 | -35 | Yes | 5.5 |
| | A181 Gilesgate | | 01:00 | 22 | 12 | -10 | Yes | 2.4 |
| | | | 02:00 | 25 | 6 | -19 | Yes | 4.8 |
| | | | 03:00 | 17 | 10 | -7 | Yes | 2.0 |
| | | | 04:00 | 17 | 21 | 4 | Yes | 0.8 |
| | | | 05:00 | 101 | 62 | -39 | Yes | 4.3 |
| | | | 06:00 | 191 | 394 | 203 | No | 11.9 |
| | | | 07:00 | 447 | 709 | 262 | No | 10.9 |
| | | | 08:00 | 470 | 689 | 219 | No | 9.1 |
| | | | 09:00 | 570 | 761 | 191 | No | 7.4 |
| | | | 10:00 | 629 | 712 | 83 | Yes | 3.2 |
| | | | 11:00 | 638 | 665 | 27 | Yes | 1.1 |
| | | | 12:00 | 644 | 729 | 85 | Yes | 3.2 |
| | | | 13:00 | 656 | 697 | 41 | Yes | 1.6 |
| | | | 14:00 | 668 | 622 | -46 | Yes | 1.8 |
| | | | 15:00 | 749 | 608 | -141 | No | 5.4 |
| | | | 16:00 | 817 | 649 | -168 | No | 6.2 |
| | | | 17:00 | 766 | 578 | -188 | No | 7.2 |
| | | | 18:00 | 650 | 601 | -49 | Yes | 2.0 |
| | | | 19:00 | 462 | 605 | 143 | No | 6.2 |
| | | | 20:00 | 326 | 421 | 95 | Yes | 4.9 |
| | | | 21:00 | 268 | 275 | 7 | Yes | 0.4 |
| | | | 22:00 | 174 | 183 | 9 | Yes | 0.7 |
| | | | 23:00 | 98 | 71 | -27 | Yes | 2.9 |
| 16 | 2382 | West | 00:00 | 47 | 19 | -28 | Yes | 4.9 |
| | A181 Gilesgate | | 01:00 | 18 | 13 | -5 | Yes | 1.3 |
| | | | 02:00 | 20 | 10 | -10 | Yes | 2.7 |
| | | | 03:00 | 21 | 9 | -12 | Yes | 3.2 |
| | | | 04:00 | 24 | 17 | -7 | Yes | 1.5 |
| | | | 05:00 | 58 | 52 | -6 | Yes | 0.8 |
| | | | 06:00 | 215 | 299 | 84 | Yes | 5.3 |
| | | | 07:00 | 494 | 810 | 316 | No | 12.4 |
| | | | 08:00 | 348 | 789 | 441 | No | 18.5 |
| | | | 09:00 | 545 | 596 | 51 | Yes | 2.1 |
| | | | 10:00 | 616 | 569 | -47 | Yes | 1.9 |
| | | | 11:00 | 624 | 573 | -51 | Yes | 2.1 |
| | | | 12:00 | 687 | 613 | -74 | Yes | 2.9 |
| | | | 13:00 | 652 | 602 | -50 | Yes | 2.0 |
| | | | 14:00 | 674 | 665 | -9 | Yes | 0.3 |
| | | | 15:00 | 651 | 744 | 93 | Yes | 3.5 |
| | | | 16:00 | 595 | 652 | 57 | Yes | 2.3 |
| | | | 17:00 | 554 | 571 | 17 | Yes | 0.7 |
| | | | 18:00 | 616 | 601 | -15 | Yes | 0.6 |
| | | | 19:00 | 504 | 516 | 12 | Yes | 0.5 |
| | | | 20:00 | 327 | 340 | 13 | Yes | 0.7 |
| | | | 21:00 | 263 | 221 | -42 | Yes | 2.7 |
| | | | 22:00 | 186 | 157 | -29 | Yes | 2.2 |
| | | | 23:00 | 90 | 38 | -52 | Yes | 6.5 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| 17 | **3032** | **South** | 00:00 | 9 | 1 | -8 | Yes | 3.6 |
| | **Margery Lane** | | 01:00 | 5 | 0 | -5 | Yes | 3.1 |
| | | | 02:00 | 2 | 1 | -1 | Yes | 1.0 |
| | | | 03:00 | 2 | 2 | 0 | Yes | 0.2 |
| | | | 04:00 | 1 | 2 | 1 | Yes | 1.2 |
| | | | 05:00 | 10 | 3 | -7 | Yes | 2.7 |
| | | | 06:00 | 28 | 29 | 1 | Yes | 0.2 |
| | | | 07:00 | 179 | 72 | -107 | No | 9.5 |
| | | | 08:00 | 267 | 83 | -184 | No | 13.9 |
| | | | 09:00 | 136 | 76 | -60 | Yes | 5.8 |
| | | | 10:00 | 119 | 38 | -81 | Yes | 9.1 |
| | | | 11:00 | 121 | 40 | -81 | Yes | 9.1 |
| | | | 12:00 | 145 | 34 | -111 | No | 11.7 |
| | | | 13:00 | 124 | 30 | -94 | Yes | 10.7 |
| | | | 14:00 | 136 | 53 | -83 | Yes | 8.5 |
| | | | 15:00 | 178 | 71 | -107 | No | 9.6 |
| | | | 16:00 | 198 | 82 | -116 | No | 9.8 |
| | | | 17:00 | 223 | 73 | -150 | No | 12.3 |
| | | | 18:00 | 149 | 29 | -120 | No | 12.7 |
| | | | 19:00 | 93 | 37 | -56 | Yes | 6.9 |
| | | | 20:00 | 77 | 23 | -54 | Yes | 7.6 |
| | | | 21:00 | 47 | 18 | -29 | Yes | 5.1 |
| | | | 22:00 | 30 | 11 | -19 | Yes | 4.2 |
| | | | 23:00 | 13 | 4 | -9 | Yes | 3.0 |
| 18 | **3032** | **North** | 00:00 | 9 | 1 | -8 | Yes | 3.5 |
| | **Margery Lane** | | 01:00 | 4 | 0 | -4 | Yes | 2.7 |
| | | | 02:00 | 1 | 1 | 0 | Yes | 0.4 |
| | | | 03:00 | 1 | 0 | -1 | Yes | 1.4 |
| | | | 04:00 | 1 | 1 | 0 | Yes | 0.4 |
| | | | 05:00 | 10 | 2 | -8 | Yes | 3.2 |
| | | | 06:00 | 22 | 23 | 1 | Yes | 0.2 |
| | | | 07:00 | 122 | 33 | -89 | Yes | 10.1 |
| | | | 08:00 | 228 | 26 | -202 | No | 17.9 |
| | | | 09:00 | 99 | 20 | -79 | Yes | 10.2 |
| | | | 10:00 | 97 | 17 | -80 | Yes | 10.6 |
| | | | 11:00 | 94 | 19 | -75 | Yes | 10.0 |
| | | | 12:00 | 105 | 12 | -93 | Yes | 12.2 |
| | | | 13:00 | 97 | 12 | -85 | Yes | 11.5 |
| | | | 14:00 | 120 | 7 | -113 | No | 14.2 |
| | | | 15:00 | 175 | 71 | -104 | No | 9.4 |
| | | | 16:00 | 239 | 104 | -135 | No | 10.3 |
| | | | 17:00 | 222 | 72 | -150 | No | 12.4 |
| | | | 18:00 | 116 | 20 | -96 | Yes | 11.6 |
| | | | 19:00 | 76 | 8 | -68 | Yes | 10.5 |
| | | | 20:00 | 47 | 7 | -40 | Yes | 7.7 |
| | | | 21:00 | 39 | 6 | -33 | Yes | 6.9 |
| | | | 22:00 | 25 | 4 | -21 | Yes | 5.5 |
| | | | 23:00 | 17 | 2 | -15 | Yes | 4.8 |
| 19 | **3972** | **South** | 00:00 | 21 | 10 | -11 | Yes | 2.9 |
| | **Church Street** | | 01:00 | 13 | 6 | -7 | Yes | 2.4 |
| | | | 02:00 | 13 | 5 | -8 | Yes | 2.8 |
| | | | 03:00 | 7 | 5 | -2 | Yes | 0.9 |
| | | | 04:00 | 5 | 7 | 2 | Yes | 1.0 |
| | | | 05:00 | 22 | 26 | 4 | Yes | 0.9 |
| | | | 06:00 | 92 | 152 | 60 | Yes | 5.5 |
| | | | 07:00 | 254 | 378 | 124 | No | 7.0 |
| | | | 08:00 | 300 | 431 | 131 | No | 6.8 |
| | | | 09:00 | 269 | 314 | 45 | Yes | 2.7 |
| | | | 10:00 | 232 | 219 | -13 | Yes | 0.9 |
| | | | 11:00 | 285 | 209 | -76 | Yes | 4.8 |
| | | | 12:00 | 303 | 238 | -65 | Yes | 4.0 |
| | | | 13:00 | 291 | 213 | -78 | Yes | 4.9 |
| | | | 14:00 | 326 | 307 | -19 | Yes | 1.1 |
| | | | 15:00 | 409 | 454 | 45 | Yes | 2.2 |
| | | | 16:00 | 424 | 447 | 23 | Yes | 1.1 |
| | | | 17:00 | 421 | 462 | 41 | Yes | 2.0 |
| | | | 18:00 | 286 | 311 | 25 | Yes | 1.4 |
| | | | 19:00 | 212 | 194 | -18 | Yes | 1.3 |
| | | | 20:00 | 163 | 152 | -11 | Yes | 0.9 |
| | | | 21:00 | 160 | 83 | -77 | Yes | 7.0 |
| | | | 22:00 | 100 | 55 | -45 | Yes | 5.1 |
| | | | 23:00 | 54 | 12 | -42 | Yes | 7.3 |
| 20 | **3972** | **North** | 00:00 | 21 | 14 | -7 | Yes | 1.7 |
| | **Church Street** | | 01:00 | 11 | 8 | -3 | Yes | 0.9 |
| | | | 02:00 | 11 | 6 | -5 | Yes | 1.7 |
| | | | 03:00 | 6 | 7 | 1 | Yes | 0.5 |
| | | | 04:00 | 6 | 7 | 1 | Yes | 0.3 |
| | | | 05:00 | 34 | 27 | -7 | Yes | 1.3 |
| | | | 06:00 | 100 | 192 | 92 | Yes | 7.6 |
| | | | 07:00 | 309 | 550 | 241 | No | 11.6 |
| | | | 08:00 | 394 | 752 | 358 | No | 15.0 |
| | | | 09:00 | 267 | 422 | 155 | No | 8.4 |
| | | | 10:00 | 233 | 291 | 58 | Yes | 3.6 |
| | | | 11:00 | 263 | 285 | 22 | Yes | 1.3 |
| | | | 12:00 | 251 | 288 | 37 | Yes | 2.3 |
| | | | 13:00 | 275 | 295 | 20 | Yes | 1.2 |
| | | | 14:00 | 265 | 335 | 70 | Yes | 4.0 |
| | | | 15:00 | 291 | 374 | 83 | Yes | 4.5 |
| | | | 16:00 | 292 | 431 | 139 | No | 7.3 |
| | | | 17:00 | 286 | 387 | 101 | No | 5.5 |
| | | | 18:00 | 262 | 313 | 51 | Yes | 3.0 |
| | | | 19:00 | 174 | 276 | 102 | No | 6.8 |
| | | | 20:00 | 101 | 154 | 53 | Yes | 4.7 |
| | | | 21:00 | 93 | 127 | 34 | Yes | 3.2 |
| | | | 22:00 | 61 | 76 | 15 | Yes | 1.9 |
| | | | 23:00 | 37 | 33 | -4 | Yes | 0.7 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| 21 | 9991 | East | 00:00 | 16 | 0 | -16 | Yes | 5.7 |
| | North Road | | 01:00 | 8 | 0 | -8 | Yes | 4.0 |
| | | | 02:00 | 6 | 0 | -6 | Yes | 3.5 |
| | | | 03:00 | 5 | 0 | -5 | Yes | 3.3 |
| | | | 04:00 | 7 | 0 | -7 | Yes | 3.7 |
| | | | 05:00 | 17 | 0 | -17 | Yes | 5.8 |
| | | | 06:00 | 46 | 0 | -46 | Yes | 9.6 |
| | | | 07:00 | 120 | 39 | -81 | Yes | 9.1 |
| | | | 08:00 | 123 | 46 | -77 | Yes | 8.4 |
| | | | 09:00 | 127 | 54 | -73 | Yes | 7.6 |
| | | | 10:00 | 123 | 21 | -102 | No | 12.0 |
| | | | 11:00 | 119 | 19 | -100 | No | 12.1 |
| | | | 12:00 | 115 | 18 | -97 | Yes | 11.9 |
| | | | 13:00 | 114 | 20 | -94 | Yes | 11.5 |
| | | | 14:00 | 114 | 19 | -95 | Yes | 11.6 |
| | | | 15:00 | 126 | 21 | -105 | No | 12.3 |
| | | | 16:00 | 134 | 50 | -84 | Yes | 8.7 |
| | | | 17:00 | 141 | 49 | -92 | Yes | 9.4 |
| | | | 18:00 | 117 | 37 | -80 | Yes | 9.1 |
| | | | 19:00 | 88 | 0 | -88 | Yes | 13.3 |
| | | | 20:00 | 71 | 0 | -71 | Yes | 11.9 |
| | | | 21:00 | 51 | 0 | -51 | Yes | 10.1 |
| | | | 22:00 | 42 | 0 | -42 | Yes | 9.1 |
| | | | 23:00 | 32 | 0 | -32 | Yes | 8.0 |
| 23 | 9992 | South | 00:00 | 18 | 19 | 1 | Yes | 0.2 |
| | A167 Darlington Road | | 01:00 | 10 | 19 | 9 | Yes | 2.3 |
| | | | 02:00 | 12 | 9 | -3 | Yes | 0.8 |
| | | | 03:00 | 8 | 13 | 5 | Yes | 1.5 |
| | | | 04:00 | 17 | 17 | 0 | Yes | 0.1 |
| | | | 05:00 | 64 | 69 | 5 | Yes | 0.6 |
| | | | 06:00 | 215 | 303 | 88 | Yes | 5.5 |
| | | | 07:00 | 554 | 647 | 93 | Yes | 3.8 |
| | | | 08:00 | 569 | 648 | 79 | Yes | 3.2 |
| | | | 09:00 | 498 | 589 | 91 | Yes | 3.9 |
| | | | 10:00 | 382 | 451 | 69 | Yes | 3.4 |
| | | | 11:00 | 409 | 420 | 11 | Yes | 0.5 |
| | | | 12:00 | 474 | 461 | -13 | Yes | 0.6 |
| | | | 13:00 | 444 | 476 | 32 | Yes | 1.5 |
| | | | 14:00 | 495 | 463 | -32 | Yes | 1.5 |
| | | | 15:00 | 565 | 501 | -64 | Yes | 2.8 |
| | | | 16:00 | 559 | 548 | -11 | Yes | 0.5 |
| | | | 17:00 | 554 | 519 | -35 | Yes | 1.5 |
| | | | 18:00 | 421 | 425 | 4 | Yes | 0.2 |
| | | | 19:00 | 326 | 507 | 181 | No | 8.9 |
| | | | 20:00 | 209 | 365 | 156 | No | 9.2 |
| | | | 21:00 | 166 | 226 | 60 | Yes | 4.3 |
| | | | 22:00 | 102 | 153 | 51 | Yes | 4.5 |
| | | | 23:00 | 51 | 55 | 4 | Yes | 0.5 |
| 24 | 9992 | North | 00:00 | 31 | 9 | -22 | Yes | 4.9 |
| | A167 Darlington Road | | 01:00 | 16 | 5 | -11 | Yes | 3.3 |
| | | | 02:00 | 17 | 9 | -8 | Yes | 2.1 |
| | | | 03:00 | 13 | 11 | -2 | Yes | 0.6 |
| | | | 04:00 | 14 | 9 | -5 | Yes | 1.6 |
| | | | 05:00 | 50 | 28 | -22 | Yes | 3.6 |
| | | | 06:00 | 230 | 288 | 58 | Yes | 3.6 |
| | | | 07:00 | 666 | 832 | 166 | No | 6.1 |
| | | | 08:00 | 773 | 791 | 18 | Yes | 0.7 |
| | | | 09:00 | 527 | 468 | -59 | Yes | 2.6 |
| | | | 10:00 | 446 | 308 | -138 | No | 7.1 |
| | | | 11:00 | 448 | 309 | -139 | No | 7.1 |
| | | | 12:00 | 463 | 283 | -180 | No | 9.3 |
| | | | 13:00 | 461 | 317 | -144 | No | 7.3 |
| | | | 14:00 | 500 | 346 | -154 | No | 7.5 |
| | | | 15:00 | 560 | 441 | -119 | No | 5.3 |
| | | | 16:00 | 629 | 899 | 270 | No | 9.8 |
| | | | 17:00 | 647 | 875 | 228 | No | 8.3 |
| | | | 18:00 | 489 | 405 | -84 | Yes | 4.0 |
| | | | 19:00 | 276 | 253 | -23 | Yes | 1.4 |
| | | | 20:00 | 195 | 158 | -37 | Yes | 2.8 |
| | | | 21:00 | 169 | 109 | -60 | Yes | 5.1 |
| | | | 22:00 | 125 | 80 | -45 | Yes | 4.4 |
| | | | 23:00 | 71 | 29 | -42 | Yes | 5.9 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| 25 | 9993 | South | 00:00 | 39 | 10 | -29 | Yes | 5.8 |
| | Alexandria Crescent | | 01:00 | 21 | 10 | -11 | Yes | 2.7 |
| | | | 02:00 | 11 | 3 | -8 | Yes | 3.0 |
| | | | 03:00 | 12 | 10 | -2 | Yes | 0.6 |
| | | | 04:00 | 16 | 16 | 0 | Yes | 0.1 |
| | | | 05:00 | 41 | 42 | 1 | Yes | 0.1 |
| | | | 06:00 | 124 | 220 | 96 | Yes | 7.3 |
| | | | 07:00 | 424 | 436 | 12 | Yes | 0.6 |
| | | | 08:00 | 475 | 549 | 74 | Yes | 3.3 |
| | | | 09:00 | 350 | 503 | 153 | No | 7.4 |
| | | | 10:00 | 358 | 400 | 42 | Yes | 2.1 |
| | | | 11:00 | 370 | 416 | 46 | Yes | 2.3 |
| | | | 12:00 | 360 | 455 | 95 | Yes | 4.7 |
| | | | 13:00 | 390 | 454 | 64 | Yes | 3.1 |
| | | | 14:00 | 413 | 528 | 115 | No | 5.3 |
| | | | 15:00 | 448 | 565 | 117 | No | 5.2 |
| | | | 16:00 | 536 | 612 | 76 | Yes | 3.2 |
| | | | 17:00 | 566 | 677 | 111 | No | 4.5 |
| | | | 18:00 | 426 | 438 | 12 | Yes | 0.6 |
| | | | 19:00 | 334 | 359 | 25 | Yes | 1.3 |
| | | | 20:00 | 259 | 195 | -64 | Yes | 4.3 |
| | | | 21:00 | 222 | 148 | -74 | Yes | 5.5 |
| | | | 22:00 | 168 | 95 | -73 | Yes | 6.4 |
| | | | 23:00 | 93 | 23 | -70 | Yes | 9.2 |
| 26 | 9993 | North | 00:00 | 34 | 21 | -13 | Yes | 2.5 |
| | Alexandria Crescent | | 01:00 | 17 | 10 | -7 | Yes | 1.8 |
| | | | 02:00 | 13 | 8 | -5 | Yes | 1.5 |
| | | | 03:00 | 11 | 10 | -1 | Yes | 0.3 |
| | | | 04:00 | 19 | 14 | -5 | Yes | 1.2 |
| | | | 05:00 | 98 | 30 | -68 | Yes | 8.5 |
| | | | 06:00 | 285 | 423 | 138 | No | 7.3 |
| | | | 07:00 | 778 | 1063 | 285 | No | 9.4 |
| | | | 08:00 | 867 | 1026 | 159 | No | 5.2 |
| | | | 09:00 | 683 | 656 | -27 | Yes | 1.1 |
| | | | 10:00 | 587 | 382 | -205 | No | 9.3 |
| | | | 11:00 | 559 | 387 | -172 | No | 7.9 |
| | | | 12:00 | 549 | 374 | -175 | No | 8.1 |
| | | | 13:00 | 534 | 415 | -119 | No | 5.4 |
| | | | 14:00 | 540 | 456 | -84 | Yes | 3.7 |
| | | | 15:00 | 601 | 580 | -21 | Yes | 0.9 |
| | | | 16:00 | 649 | 728 | 79 | Yes | 3.0 |
| | | | 17:00 | 671 | 746 | 75 | Yes | 2.8 |
| | | | 18:00 | 572 | 534 | -38 | Yes | 1.6 |
| | | | 19:00 | 412 | 340 | -72 | Yes | 3.7 |
| | | | 20:00 | 264 | 247 | -17 | Yes | 1.1 |
| | | | 21:00 | 217 | 171 | -46 | Yes | 3.3 |
| | | | 22:00 | 148 | 131 | -17 | Yes | 1.4 |
| | | | 23:00 | 88 | 42 | -46 | Yes | 5.7 |
| 27 | 2499 | East | 00:00 | 23 | 1 | -22 | Yes | 6.4 |
| | CLAYPATH DURHAM [Bet A690 & | | 01:00 | 18 | 3 | -15 | Yes | 4.6 |
| | | | 02:00 | 10 | 0 | -10 | Yes | 4.5 |
| | | | 03:00 | 6 | 1 | -5 | Yes | 2.6 |
| | | | 04:00 | 6 | 3 | -3 | Yes | 1.3 |
| | | | 05:00 | 7 | 7 | 0 | Yes | 0.0 |
| | | | 06:00 | 27 | 32 | 5 | Yes | 0.9 |
| | | | 07:00 | 135 | 40 | -95 | Yes | 10.2 |
| | | | 08:00 | 224 | 38 | -186 | No | 16.2 |
| | | | 09:00 | 222 | 74 | -148 | No | 12.2 |
| | | | 10:00 | 239 | 90 | -149 | No | 11.6 |
| | | | 11:00 | 250 | 91 | -159 | No | 12.2 |
| | | | 12:00 | 281 | 108 | -173 | No | 12.4 |
| | | | 13:00 | 271 | 97 | -174 | No | 12.8 |
| | | | 14:00 | 274 | 181 | -93 | Yes | 6.1 |
| | | | 15:00 | 324 | 348 | 24 | Yes | 1.3 |
| | | | 16:00 | 367 | 344 | -23 | Yes | 1.2 |
| | | | 17:00 | 350 | 271 | -79 | Yes | 4.5 |
| | | | 18:00 | 205 | 157 | -48 | Yes | 3.5 |
| | | | 19:00 | 152 | 71 | -81 | Yes | 7.7 |
| | | | 20:00 | 121 | 53 | -68 | Yes | 7.3 |
| | | | 21:00 | 78 | 34 | -44 | Yes | 5.9 |
| | | | 22:00 | 75 | 21 | -54 | Yes | 7.8 |
| | | | 23:00 | 55 | 4 | -51 | Yes | 9.4 |
| 28 | 2499 | West | 00:00 | 10 | 3 | -7 | Yes | 2.7 |
| | CLAYPATH DURHAM [Bet A690 & | | 01:00 | 6 | 0 | -6 | Yes | 3.5 |
| | | | 02:00 | 5 | 1 | -4 | Yes | 2.2 |
| | | | 03:00 | 4 | 2 | -2 | Yes | 1.2 |
| | | | 04:00 | 1 | 1 | 0 | Yes | 0.3 |
| | | | 05:00 | 7 | 8 | 1 | Yes | 0.4 |
| | | | 06:00 | 28 | 76 | 48 | Yes | 6.6 |
| | | | 07:00 | 132 | 189 | 57 | Yes | 4.5 |
| | | | 08:00 | 218 | 190 | -28 | Yes | 1.9 |
| | | | 09:00 | 176 | 135 | -41 | Yes | 3.3 |
| | | | 10:00 | 139 | 62 | -77 | Yes | 7.7 |
| | | | 11:00 | 129 | 65 | -64 | Yes | 6.5 |
| | | | 12:00 | 137 | 76 | -61 | Yes | 5.9 |
| | | | 13:00 | 118 | 69 | -49 | Yes | 5.1 |
| | | | 14:00 | 123 | 83 | -40 | Yes | 3.9 |
| | | | 15:00 | 123 | 87 | -36 | Yes | 3.5 |
| | | | 16:00 | 139 | 100 | -39 | Yes | 3.5 |
| | | | 17:00 | 129 | 82 | -47 | Yes | 4.5 |
| | | | 18:00 | 105 | 68 | -37 | Yes | 3.9 |
| | | | 19:00 | 77 | 52 | -25 | Yes | 3.2 |
| | | | 20:00 | 52 | 48 | -4 | Yes | 0.5 |
| | | | 21:00 | 44 | 27 | -17 | Yes | 2.9 |
| | | | 22:00 | 31 | 13 | -18 | Yes | 3.8 |
| | | | 23:00 | 27 | 6 | -21 | Yes | 5.2 |

## 9.3 Appendix C

**Public Sector Mosaic Groups and Types (Experian, 2009).**

| Group | Description | % (people) | % (households) | Type | Description | % (people) | % (households) |
|---|---|---|---|---|---|---|---|
| A | Residents of isolated rural communities | 4.72 | 4.40 | A01 | Rural families with high incomes, often from city jobs | 0.99 | 0.85 |
| | | | | A02 | Retirees electing to settle in environmentally attractive localities | 1.26 | 1.31 |
| | | | | A03 | Remote communities with poor access to public and commercial services | 0.87 | 0.87 |
| | | | | A04 | Villagers with few well paid alternatives to agricultural employment | 1.59 | 1.36 |
| B | Residents of small and mid-sized towns with strong local roots | 8.89 | 8.75 | B05 | Better off empty nesters in low density estates on town fringes | 2.39 | 2.96 |
| | | | | B06 | Self employed trades people living in smaller communities | 2.57 | 1.99 |
| | | | | B07 | Empty nester owner occupiers making little use of public services | 2.72 | 2.63 |
| | | | | B08 | Mixed communities with many single people in the centres of small towns | 1.14 | 1.17 |
| C | Wealthy people living in the most sought after neighbourhoods | 4.22 | 3.54 | C09 | Successful older business leaders living in sought-after suburbs | 1.85 | 1.50 |
| | | | | C10 | Wealthy families in substantial houses with little community involvement | 0.68 | 0.56 |
| | | | | C11 | Creative professionals seeking involvement in local communities | 1.42 | 1.18 |
| | | | | C12 | Residents in smart city centre flats who make little use of public services | 0.29 | 0.30 |
| D | Successful professionals living in suburban or semi-rural homes | 9.32 | 8.23 | D13 | Higher income older champions of village communities | 2.47 | 2.31 |
| | | | | D14 | Older people living in large houses in mature suburbs | 1.71 | 1.84 |
| | | | | D15 | Well off commuters living in spacious houses in semi rural settings | 2.21 | 1.77 |
| | | | | D16 | Higher income families concerned with education and careers | 2.90 | 2.30 |
| E | Middle income families living in moderate suburban semis | 13.39 | 11.18 | E17 | Comfortably off suburban families weakly tied to their local community | 2.85 | 2.14 |
| | | | | E18 | Industrial workers living comfortably in owner occupied semis | 2.98 | 2.73 |
| | | | | E19 | Self reliant older families in suburban semis in industrial towns | 2.31 | 2.63 |
| | | | | E20 | Upwardly mobile South Asian families living in inter war suburbs | 1.54 | 0.98 |
| | | | | E21 | Middle aged families living in less fashionable inter war suburban semis | 3.80 | 2.70 |
| F | Couples with young children in comfortable modern housing | 5.59 | 5.78 | F22 | Busy executives in town houses in dormitory settlements | 1.10 | 1.67 |
| | | | | F23 | Early middle aged parents likely to be involved in their children's education | 2.81 | 2.42 |
| | | | | F24 | Young parents new to their neighbourhood, keen to put down roots | 1.50 | 1.52 |
| | | | | F25 | Personnel reliant on the Ministry of Defence for public services | 0.24 | 0.17 |
| G | Young, well-educated city dwellers | 8.18 | 8.48 | G26 | Well educated singles living in purpose built flats | 1.30 | 1.09 |
| | | | | G27 | City dwellers owning houses in older neighbourhoods | 0.60 | 0.57 |
| | | | | G28 | Singles and sharers occupying converted Victorian houses | 0.54 | 0.53 |
| | | | | G29 | Young professional families settling in better quality older terraces | 1.71 | 1.68 |
| | | | | G30 | Diverse communities of well educated singles living in smart, small flats | 0.41 | 0.52 |
| | | | | G31 | Owners in smart purpose built flats in prestige locations, many newly built | 0.76 | 1.00 |
| | | | | G32 | Students and other transient singles in multi-let houses | 1.01 | 0.93 |
| | | | | G33 | Transient singles, poorly supported by family and neighbours | 1.02 | 1.03 |
| | | | | G34 | Students involved in college and university communities | 0.74 | 1.14 |
| H | Couples and young singles in small modern starter homes | 4.01 | 5.91 | H35 | Childless new owner occupiers in cramped new homes | 1.51 | 2.37 |
| | | | | H36 | Young singles and sharers renting small purpose built flats | 1.02 | 1.79 |
| | | | | H37 | Young owners and rented developments of mixed tenure | 1.15 | 1.38 |
| | | | | H38 | People living in brand new residential developments | 0.30 | 0.37 |
| I | Lower income workers in urban terraces in often diverse areas | 6.84 | 7.02 | I39 | Young owners and private renters in inner city terraces | 0.36 | 0.34 |
| | | | | I40 | Multi-ethnic communities in newer suburbs away from the inner city | 0.53 | 0.58 |
| | | | | I41 | Renters of older terraces in ethnically diverse communities | 0.53 | 0.52 |
| | | | | I42 | South Asian communities experiencing social deprivation | 1.26 | 0.88 |
| | | | | I43 | Older town centre terraces with transient, single populations | 1.67 | 2.72 |
| | | | | I44 | Low income families occupying poor quality older terraces | 2.52 | 1.97 |
| J | Owner occupiers in older-style housing in ex-industrial areas | 7.32 | 7.40 | J45 | Low income communities reliant on low skill industrial jobs | 2.88 | 3.09 |
| | | | | J46 | Residents in blue collar communities revitalised by commuters | 2.36 | 2.06 |
| | | | | J47 | Comfortably off industrial workers owning their own homes | 2.07 | 2.25 |
| K | Residents with sufficient incomes in right-to-buy social housing | 11.07 | 8.67 | K48 | Middle aged couples and families in right-to-buy homes | 1.89 | 1.72 |
| | | | | K49 | Low income older couples long established in former council estates | 2.07 | 2.06 |
| | | | | K50 | Older families in low value housing in traditional industrial areas | 3.67 | 2.68 |
| | | | | K51 | Often indebted families living in low rise estates | 3.47 | 2.20 |
| L | Active elderly people living in pleasant retirement locations | 3.10 | 4.34 | L52 | Communities of wealthy older people living in large seaside houses | 0.46 | 0.67 |
| | | | | L53 | Residents in retirement, second home and tourist communities | 0.51 | 0.60 |
| | | | | L54 | Retired people of modest means commonly living in seaside bungalows | 1.28 | 1.79 |
| | | | | L55 | Capable older people leasing / owning flats in purpose built blocks | 0.82 | 1.29 |
| M | Elderly people reliant on state support | 3.84 | 5.96 | M56 | Older people living on social housing estates with limited budgets | 1.92 | 2.68 |
| | | | | M57 | Old people in flats subsisting on welfare payments | 0.81 | 1.31 |
| | | | | M58 | Less mobile older people requiring a degree of care | 0.46 | 0.86 |
| | | | | M59 | People living in social accommodation designed for older people | 0.61 | 1.12 |
| N | Young people renting flats in high density social housing | 4.46 | 5.18 | N60 | Tenants in social housing flats on estates at risk of serious social problems | 0.64 | 0.80 |
| | | | | N61 | Childless tenants in social housing flats with modest social needs | 1.31 | 1.77 |
| | | | | N62 | Young renters in flats with a cosmopolitan mix | 0.52 | 0.50 |
| | | | | N63 | Multicultural tenants renting flats in areas of social housing | 0.50 | 0.49 |
| | | | | N64 | Diverse homesharers renting small flats in densely populated areas | 0.84 | 0.61 |
| | | | | N65 | Young singles in multi-ethnic communities, many in high rise flats | 0.33 | 0.50 |
| | | | | N66 | Childless, low income tenants in high rise flats | 0.34 | 0.50 |
| O | Families in low-rise social housing with high levels of benefit need | 5.05 | 5.16 | O67 | Older tenants in low rise social housing estates where jobs are scarce | 1.90 | 2.30 |
| | | | | O68 | Families with varied structures living in low rise social housing estates | 1.12 | 1.05 |
| | | | | O69 | Vulnerable young parents needing substantial state support | 2.08 | 1.80 |