Quantifying transport sustainability: Development of an index

Marzieh Reisi Varzaneh

Submitted in total fulfilment of the requirement of the degree of Doctor of Philosophy

June 2014

Department of Infrastructure Engineering

The University of Melbourne

Abstract

Quantifying sustainability of urban transport is important as evidenced by a growing number of studies working on measuring sustainability in transportation. This thesis first reviewed major initiatives reported in the current literature, which dealt with the challenge of measuring transport sustainability using long lists of indicators. To overcome the issue of using large number of indicators for evaluation, this thesis developed a method for obtaining a composite transport sustainability index based on three aspects: environmental, social and economic, each one defined by a set of indicators. Ten sustainability indicators relevant to urban transport were selected by assessing and reviewing the past research and based on available data for Melbourne. These indicators, which can be categorised as environmental, social and economic indicators, are depletion of non-renewable resources, GHG emissions, other air pollutants related to transport, land consumption by transport, accessibility, fatalities and injuries related to traffic accidents, mortality effects of air pollutants, car ownership costs and operation costs of public transport, vehicle and general costs of accidents and benefits of walking and cycling. To quantify selected indicators, land use/transport interaction model was developed to estimate car ownership, vehicle kilometre travelled (VKT) and modal split, and consequently transport energy consumption, emissions and its related social and economic impacts. In the next step, the indicators were integrated into transportation environmental impact index (TEII), transportation social impact index (TSII), transportation economic impact index (TCII) and then into transport sustainability index (I_{CST}) in a way that overcomes the limitations of normalisation, weighting and aggregation methods. In the final step, transport sustainability indices were developed for three different urban planning scenarios (base-case scenario, activity-centres scenario, fringe-focus scenario) for 2030, to find the most appropriate approach for urban development in the future. Indices based on the method developed in this study could help organisations for better understanding of the measures and activities that influence the sustainability of urban transport.

Declaration

I certify that:

i. the thesis comprises only my original work towards the degree of Doctor of Philosophy,
ii. due acknowledgement has been made in the text to all other material used,
iii. the thesis is fewer than 100,000 words in length, exclusive of tables, maps, bibliographies and appendices.

Marzieh Reisi Varzaneh

24 June 2014

Preface

Publications arising from the thesis are as follows:

- Reisi, M., Aye, L., Rajabifard, A., Ngo, T., 2014, Implication of land use and socio-economic factors on transport sustainability, *International Journal of Urban Planning and Transportation*. pp.1-16.
- Reisi, M., Aye, L., Rajabifard, A., Ngo, T., 2014, Transport sustainability index: Melbourne case study, *Ecological Indicators*. vol. 43, 288-296.
- Reisi, M., 2013, Sustainable transport, spatial data infrastructure Asia & Pacific Newsletter, vol. 10, no.4. pp.3-4.
- Reisi, M., Aye, L., Rajabifard, A., Ngo, T., Urban structure and transport–Melbourne case study, The 11th International Conference on Traffic & Transport Engineering, February 2012, Tehran, Iran. pp.1-10.

Acknowledgements

Over the four years journey of my research, I have received valuable helps from a large number of people. It is a great pleasure to express my thanks to many people who help me in some ways to complete this thesis.

Thanks foremost to my beloved family, for their love and supports during my PhD. Thanks to my supervisor, Associate Professor Lu Aye, for support and guidance throughout this long journey. Thanks also to my co-supervisors, Professor Abbas Rajabifard for his extensive encouragement, patience, and support that help shape my research, and Dr Tuan Ngo for his advices. Thanks to Dr Peter Rickwood for his advices on various matters relating to this thesis. Thanks to Dr Javad Ghafouri particularly for advices in some of the mathematics in Chapter 3.

Contents

List of Tables

List of Figures

The earth provides enough to satisfy every person's need but not every person's greed…When we take more than we need we are simply taking from each other, borrowing from the future, or destroying the environment and other species.

Mahatma Gandhi, Principle of Enoughness (VTPI 2010)

Chapter 1

Introduction

This thesis is concerned with the possible effects of urban planning on sustainable transport. More specifically, it explores the impact of land-use and socio-economic factors on travel behaviour. Land-use planning influences travel behaviour and consequently its environmental, social and economic impacts. Despite vast research on the effects of land use on travel behaviour, there is a lack of investigation on the effects of land use on transport sustainability and therefore are investigated in this thesis. Before narrowing the topic, a broader context is provided in this chapter, which gives a better understanding about the overall concept and the importance of the topic.

1.1. Sustainable development and transport sustainability

The concept of sustainable development was first introduced in the 'Bruntland report', published by *World Commission on Environment and Development* in 1987. It defined sustainable development as 'development that meets the needs of the present without compromising the ability of future generations to meet their own needs' (Beckerman 2007). Although there is no precise definition for sustainability after long years of its introduction

(Sahely et al. 2005), it always considers the future (Loucks 1997). Sustainability is the intersection of environmental, social and economic goals, which is called ‘Three-Ring Circus’ model (Figure 1.1) (Levett 1998; Sahely et al. 2005).

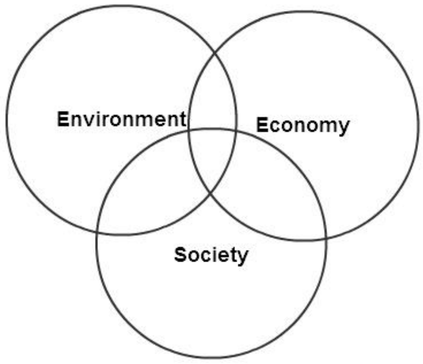


Figure 1.1.‘Three- Ring Circus’ model (Levett 1998)

The concept of sustainable transport has been developed to make a balance between transport socio-economic benefits and its social and environmental adverse effects (Janic 2006). There is no globally accepted definition for sustainable transport. OECD defined environmentally sustainable transport as ‘transportation that does not endanger public health or ecosystems and meets the needs for access consistent with:

- sustainable use of renewable resources at below their rates of regeneration
- use of non-renewable resources at below the rates of development of renewable substitutes’ (EA 1999).

Based on the principle of sustainable development, some sub-objectives can be defined for sustainable urban transport. These sub-objectives are:

- economic efficiency
- liveable streets and neighbourhoods
- protection of environment
- social equity
- safety
- contribution to economic growth (Behrends et al. 2008).

So environmental sustainability, economics efficiency and social equity must be considered in sustainable transport studies. As there is a large number of components involved in transport systems, sustainable transport is a multi-dimensional issue and its assessment is challenging (Janic 2006).

1.2. Land-use policy and transport

The principal motivation for investigation in the current study is the still ongoing debate about the effects of land-use policies on transport. There is a strong link between land use and transport. Cities would look different if fast transport modes are not available. For example, population, dispersion, and location of each part of the city might change. Transport improvement changes people's and industries locations. On the other hand, changes in land development would result in new travel patterns. People with cars can reach parts of the city that are inaccessible by public transport and walking, so by increasing the number of people who own cars; cities will expand. Therefore, the link between land use and transport is important because it affects transport and land-use policies and it must be considered for precise consideration of land-use and transport policies (Webster et al. 1990).

Interests in the role of land-use planning on transport date back to the 1980s with Newman and Kenworthy as the first researchers in this area (Rickwood 2009). There are two popular theories about the effects of urban form on transport. The first one is the 'compact city theory', which claims that a compact city results in close proximity to workplaces, facilities and public transport services and consequently in low-energy consumption for travel. On the other hand, according to the 'dispersed city theory', population density increases congestion and reduces environmental quality (Alford et al. 2008; Holden et al. 2005). This study tries to consider these theories under different urban-planning scenarios for Melbourne in 2030.

Population density is the most common factor of land use that is used in land-use/transport interaction studies (Zhang et al. 2006). Although some studies use population density as a useful factor for showing lower automobile ownership and use (Zhang et al. 2006), some other researchers argued that the relationship between land use and transport is so complex that factors such as population density alone are not good enough for estimating transport volume; that there is a need for more sophisticated measures of urban structure such as distance from Central Business District (CBD), land-use mix, dwelling types, and land consumption for transport infrastructure (Alford et al. 2008; Giuliano et al. 2006; Hess et al. 2002; Lindsey et al. 2011; Soltani & Allan 2005; Zhang et al. 2006).

Despite large studies about land-use effects on transport, some studies disagreed this relationship and argued that travel preference, socio-economic factors, engine technology, taxes on driving and fuel, and road-toll price are more influential than urban planning in transport energy consumption reduction (Næss 2009). Gender, age, household type, and household annual income are among socio-economic factors that were argued as effective predictive factors on travel behaviour (Button et al. 1980; Dargay et al. 2003; Giuliano et al. 2006; Næss 2009; Paravantis et al. 2007; Whelan et al. 2010).

So from the evidence presented, it is obvious that debate over land-use effects on transport is still active. Even if it is concluded that land-use policy can be used as a tool to influence travel behaviour, there is a need to consider how it can affect sustainable transport, which will be considered in this study.

1.3. Sustainability measurement

The sustainable indicators that were first brought up at the *United Nations Conference on Environment and Development* (UNCED) held in Rio de Janeiro in 1992, are used as important tools for measuring different aspects of sustainable development (Dobranskyte-Niskota et al. 2007). Indicators facilitate communication among scientists, policymakers, and the public because they provide high volume of information in a simple form that is easier to interpret and understand (Alberti 1996). They break down the complex concept into small and manageable units of information, so they can easily capture different aspects of transport sustainability (Castillo et al. 2010). Current sustainability studies deal with the challenge of measuring transport sustainability using long lists of sustainable indicators. Since using too many indicators is inappropriate and complex for decision making because of their hard interpretation, integrating different indicators into a single index is useful. Aggregating individual indicators into a composite index is a practical approach for sustainability evaluation (Dur et al. 2010). It measures multi-dimensional aspects of sustainability that cannot be captured completely by individual indicators alone (Saisana 2011; Zhou et al. 2007). Although many attempts were done to identify sustainable transport indicators, limited number of studies aggregate different indicators into a single index.

1.4. Research questions

Despite considerable emphasis on the effects of land-use planning on travel behaviour, there is a lack of integrated land-use/transport model and effective sustainable transport index in environmental, social and economic aspects for different urban-planning scenarios. With regards to the identified knowledge gaps, the current study will attempt to answer the following question:

- How does land-use policy influence household travel behaviour and consequently environmental, social and economic sustainability in transport?

The above question is the broad research question which can be usefully addressed by dividing it into smaller and more specific questions as follow:

Specific Question 1: How does land-use policy influence household travel behaviour (and resulting energy use)?

Specific Question 2: How does land-use policy influence social and economic aspects of travel?

Specific Question 3: How does land-use policy affect transport environmental, social and economic sustainability?

1.5. Research aim and objectives

This research aims to develop transport related environmental, social and economic indices for different urban-development scenarios. These indices will be used to assess selected urban-planning strategies and their effects on transport sustainability. To achieve the aim of the research, the following objectives were set:

1. identify and select relevant transport indicators (environmental, social and economic);
2. develop an integrated model for greenhouse gas (GHG) emissions estimation, and quantify other environmental indicators based on the integrated model;
3. quantify social and economic indicators using the results of the integrated model as a preliminary input;
4. normalise indicators and verify their weights to derive indices;
5. predict transportation environmental impact index (TEII), transportation social impact index (TSII), transportation economic impact index (TCII) and composite transport sustainability index (I_{CST}) for different urban-development scenarios for Melbourne Statistical Local Areas in 2030.

1.6. Research method

To achieve research aim and objectives, 10 environmental, social and economic indicators were selected. Different numbers of socio-economic and land-use factors were used to investigate the role of planning policies on car ownership, vehicle kilometres travelled (VKT), modal split and consequently transport energy consumption and emissions, as selected environmental indicators. Since planning policies are difficult to characterise directly, some variables that are indicative of planning-policy approaches (such as population density, accessibility measures, area size, and dwelling type) were used in the analyses.

A list of transport social and economic indicators was also developed, using different techniques for their quantification. Using appropriate normalisation, weighting and aggregation methods, transport environmental, social and economic indices were developed for different urban-planning scenarios. Main steps for achieving the thesis aim and objectives are shown in Figure1.2.

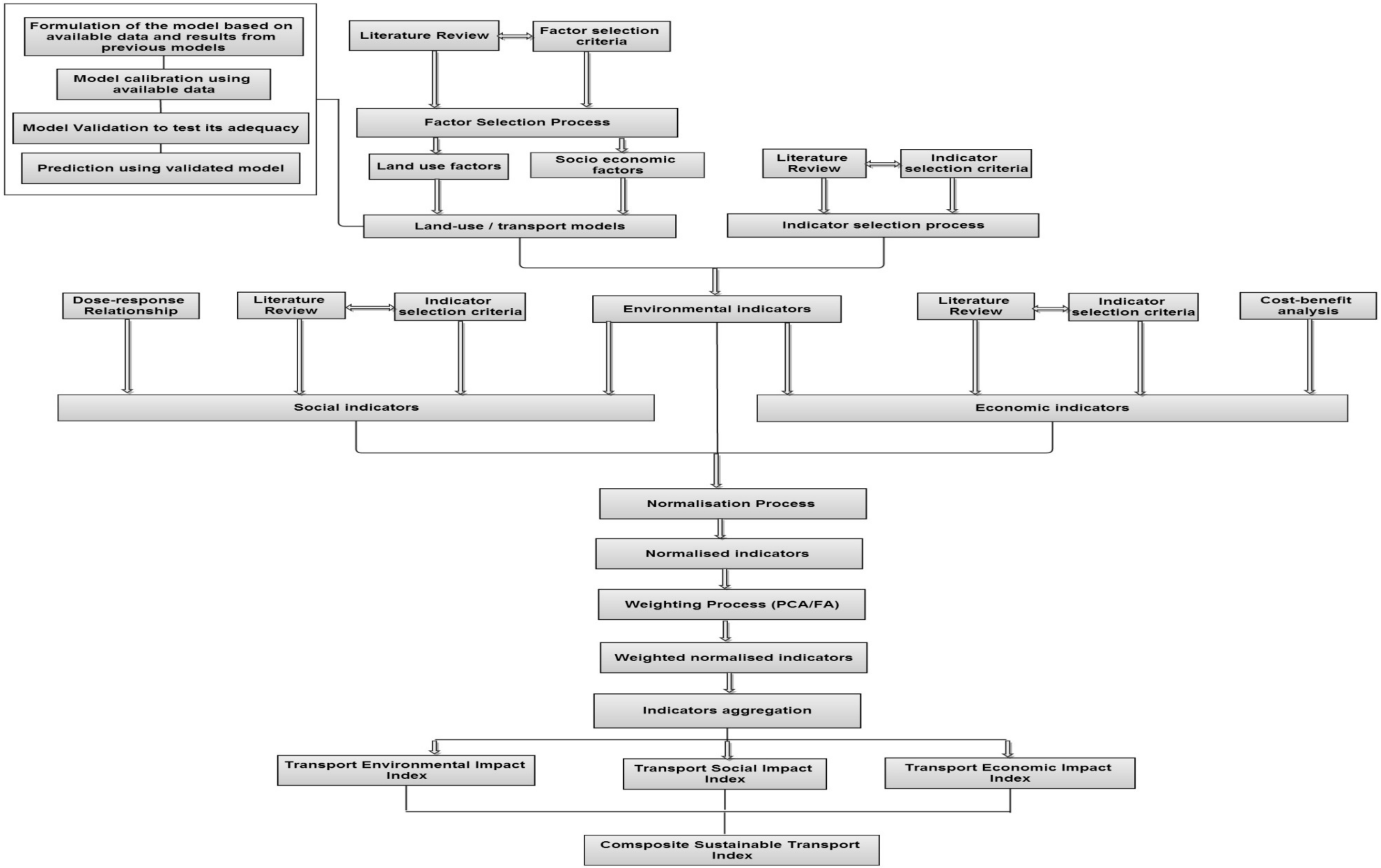


Figure 1.2. Main steps for achieving aim and objectives

1.7. Structure of the thesis

The structure of the thesis is shown in Figure 1.3. Chapter 2 contains a broad review of the literature; Chapter 3 contains environmental indicators quantification. Chapter 4 presents detailed analysis of transport social and economic indicators and their quantification. In Chapter 5, transport indices are developed, considering the most appropriate normalisation, weighting and aggregation techniques. Chapter 6 and 7 consider three urban-planning scenarios in 2030. Chapter 8 summarises the main findings of the thesis, and contains some summary discussion and conclusions.

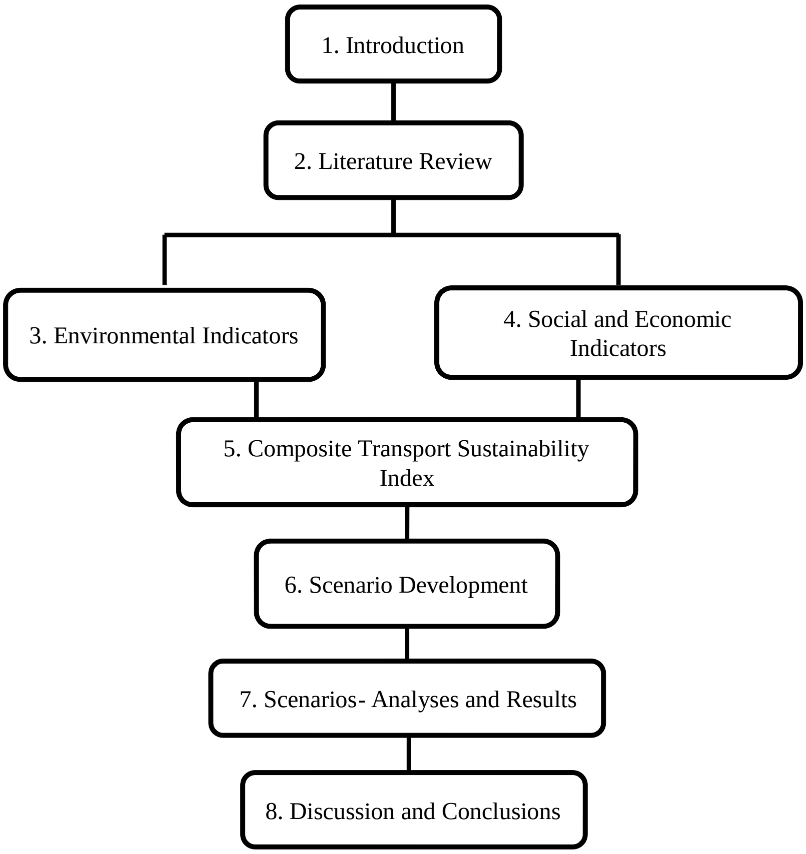


Figure 1.3. Structure of the thesis

1.8. Thesis study area: Melbourne, Australia

As Melbourne is analysed in this thesis, some familiarity with Melbourne and its geography is required (Figure 1.4). The city of Melbourne is located on the south-east coast of Australia, on the northern edge of Port Phillip Bay. The study area contained 79 statistical local areas (SLA) identified by the Australian Bureau of Statistics (ABS). The topography and climate make Melbourne an area of high air pollution potential (EPA 2000). In Melbourne, 51 billion kilometres are travelled annually by passengers, with 75.4% of those are by cars, 9.1% are by public transport, 13.1% are by walking and 2% are by cycling (Alford et al. 2008; DOT 2007). With motor vehicles as a significant source of air pollutants (83% of CO, 16% of PM_{10}, 63% of NO_X, 13% of SO_2, 41% of VOC, and 97% of lead and compounds are related to motor vehicles in Melbourne (Brindle et al. 1999)), transport sustainability issue needs special attention in this area. The main source of datasets used in this study was the Victorian Integrated Survey of Travel and Activity 2007 (VISTA07). VISTA 07 is a comprehensive survey of how, where and why Victorians travel. The data was collected from May 2007 to June 2008 from 17,100 randomly selected households in Victoria, Australia. All members of the surveyed households were asked to fill in a travel diary for one specified day of the year. The datasets also included information on household socio-economic characters using data from Australian Bureau of Statistics 2007. Data about public transport and land use were provided by Australian Department of Transport and the University of Melbourne.

In the next chapter, vast literature review was undertaken to identify the knowledge gaps. Chapter 2 extensively considered transport and its effects, urban form effects on transport, and the procedure of measuring transport sustainability. At the end of the chapter, three major gaps in the current pool of knowledge were identified.

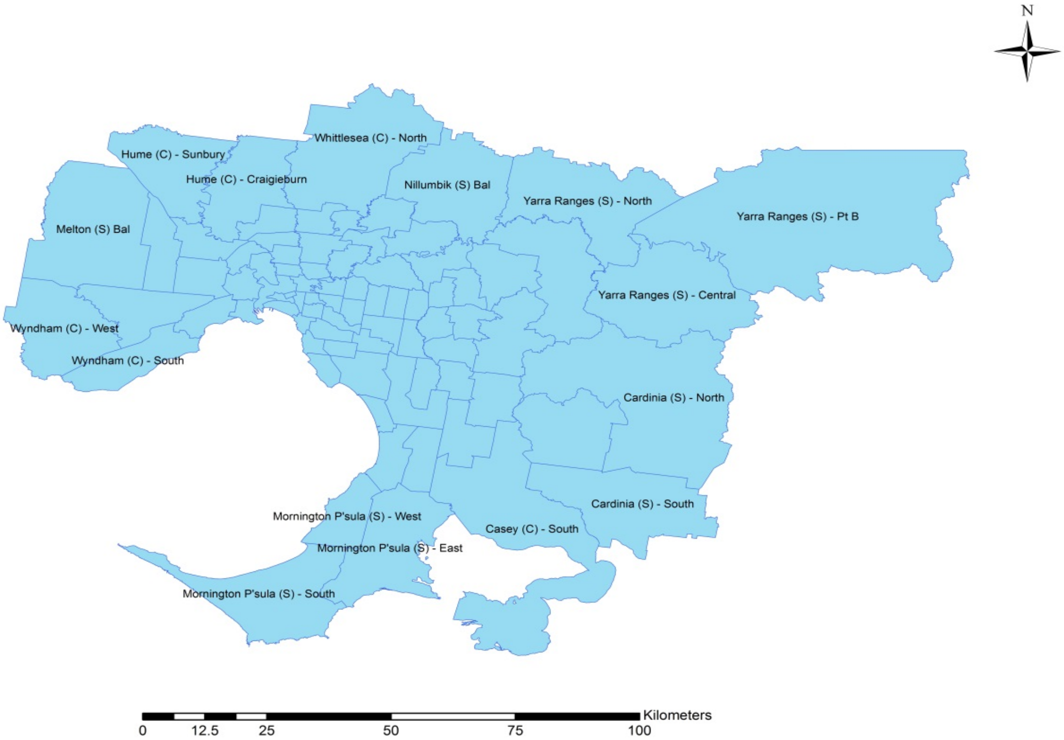


Figure 1.4. Study area

Chapter 2

Transport Sustainability and Related Studies

This chapter summarises the importance of studies and research that have been done to date on transport sustainability, land-use policy, and transport sustainable index, which helps in identifying knowledge gaps where more research is needed. First some information is provided about transport and its effects. Then, a discussion is provided about land-use planning and its effect on transport. Finally transport sustainability measurement is discussed. To avoid repetition, some additional materials not covered in this chapter, will be covered later in Chapter 3, 4, and 5.

2.1. Introduction

During the last 10 years, the term sustainable development has emerged with global priority, offering a new perspective on how to advance economic development, as well as protecting environment and increase life quality for the current and future generation (Sahely et al. 2005). The transportation sector, which has large environmental, social and economic impacts, plays a significant role in sustainable development (Dobranskyte-Niskota et al. 2007; Kolak et al. 2011). The environmental impact of transport is significant because it uses most of the world's petroleum, which produces air pollutants, including nitrous oxides, particulates, and carbon dioxide. These pollutants are significant contributors to global warming and causes severe health effects and economic costs (Dobranskyte-Niskota et al. 2007). Negative environmental and social impacts of transport impose large costs on society. It is estimated that air pollution, noise and accident related costs are at least 5% of GDP for industrialised countries (Verhoef et al. 2001).

Since the introduction of the sustainability concept, professionals have tried to define and quantify sustainability (Loucks 1997). Despite the importance of quantifying transport sustainability, fewer numbers of studies considered sustainable transport in particular compared to a large number of studies considered sustainable development in general. This chapter reviews pool of knowledge related to transport sustainability.

2.2. Transport and its effects

Sustainable transport becomes an important concern in the world because of environmental problems (Yigitcanlar et al. 2008). Despite its role on national economy, transport has different negative environmental impacts such as global warming, decreasing of the ozone layer, spread of toxic substances, decreasing of fossil fuels and other natural resources, and causing damages to landscapes and soil. A great deal of efforts has been done to reduce the impact of transport by pollution control and fuel efficiency. But increase in car ownership and use reduces the effects of these efforts. It seems that nowadays transportation is unsustainable and is becoming more unsustainable (Kahn Ribeiro et al. 2007; Shunping et al. 2009).

In Australian cities, cars are one of the major sources of energy consumption (Rickwood et al. 2008) (Figure 2.1). Motor vehicles produces about one-fifth of the CO_2 in the atmosphere that rises from human activities, one-third of CFCs, and half of nitrogen oxides. These three significant gases are major contributors to climate change (OECD 1996).

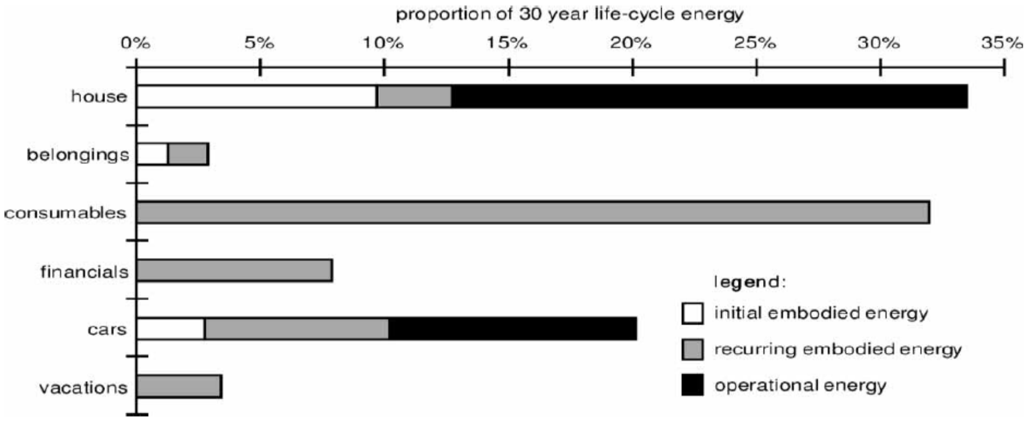


Figure 2.1. Proportion of primary energy consumed in the different activities for a chosen Australian household (Rickwood et al. 2008)

It seems that the world's energy consumption for transportation increases about 2% each year and it is estimated that by 2030, total transport energy consumption and greenhouse gas emissions (GHG) will rise up by 80% (Kahn Ribeiro et al. 2007). As shown in Figure 2.2 in 2007, 14% of the total GHG production in Australia was from transportation, and road-based transport was responsible for 12.3% of the total GHG production (Trubka et al. 2010). In Victoria, about 20 million tonnes of GHG emissions in 2006 was attributed to transport. In Melbourne, 51 billion kilometres were travelled annually by passengers (Alford et al. 2008; DOT 2007) and 83% of CO, 16% of PM_{10}, 63% of NO_x, 13% of SO_2, 41% of VOC, and 97% of lead and compounds were related to motor vehicles in this city (Brindle et al. 1999).

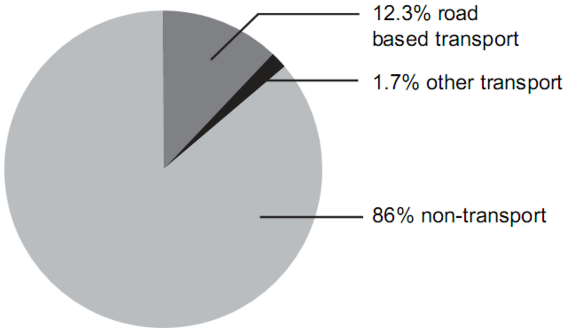


Figure 2.2. Transport's portion of Australia GHG emissions (Trubka et al. 2010)

2.3. Urban form effects on transport

Cities are major users of natural resources and the major producers of pollutants and wastes. So if cities are designed and managed in a way that resource consumption and emitted pollutants are reduced, then a major contribution to solve a global problem is achieved (Newton 1997). In 1800s, cities had high population densities and mixed land uses and consequently walking was the predominant mode of travel. In the late 1800s and early 1900s, using public transport allowed more dispersed and segregated land use. Although outer suburbs provided a quiet neighbourhood for residents, suburbanisation had several negative effects such as increase in car use, traffic noise, transport fuels consumption, and local and global air emissions (Kanaroglou et al. 2001). Since then land-use planning has received considerable attention as a factor that affects travel behaviour by changing where people live, availability of transport facilities, and other attributes of cities. Without fast modes of transport, cities will look different. For example, some parts would have a smaller population, some would not disperse nor build in low densities and even their locations might change. Improvements in transport change people's and industries' locations. Similarly changes in land development will result in new travel patterns (Webster et al. 1990).

The interrelationship between urban form and transportation has been discussed for a long time (Yigitcanlar et al. 2008). The work of Newman and Kenworthy (1989) on 32 cities brought the idea of density effect on travel behaviour. This study is still one of the most comprehensive studies on the effect of urban form on travel behaviour. Vehicle kilometre travelled (VKT) and energy consumption decrease by increasing density, while public transport use increases with density (Figure 2.3 and 2.4).

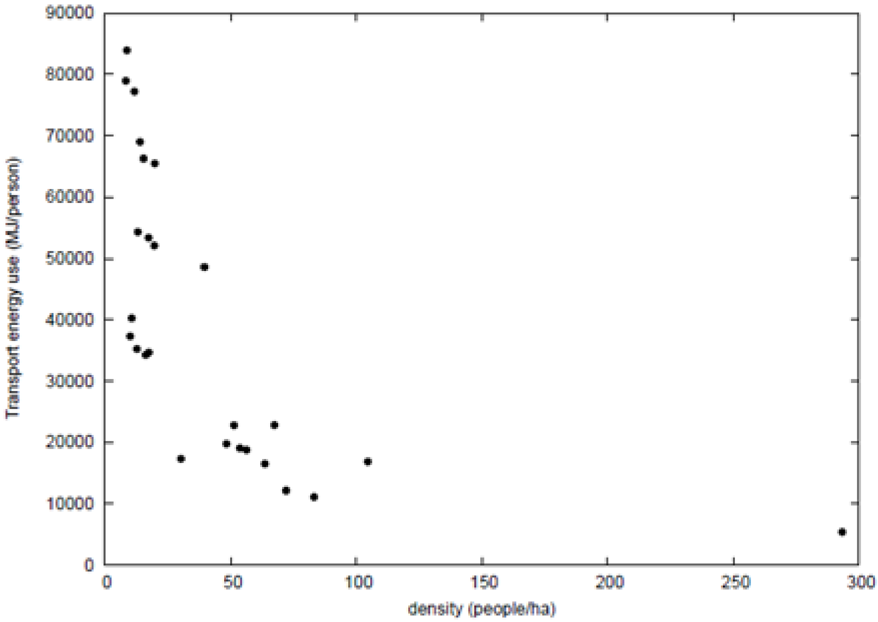


Figure 2.3. Urban density and transport energy consumption (Newman & Kenworthy 1989)

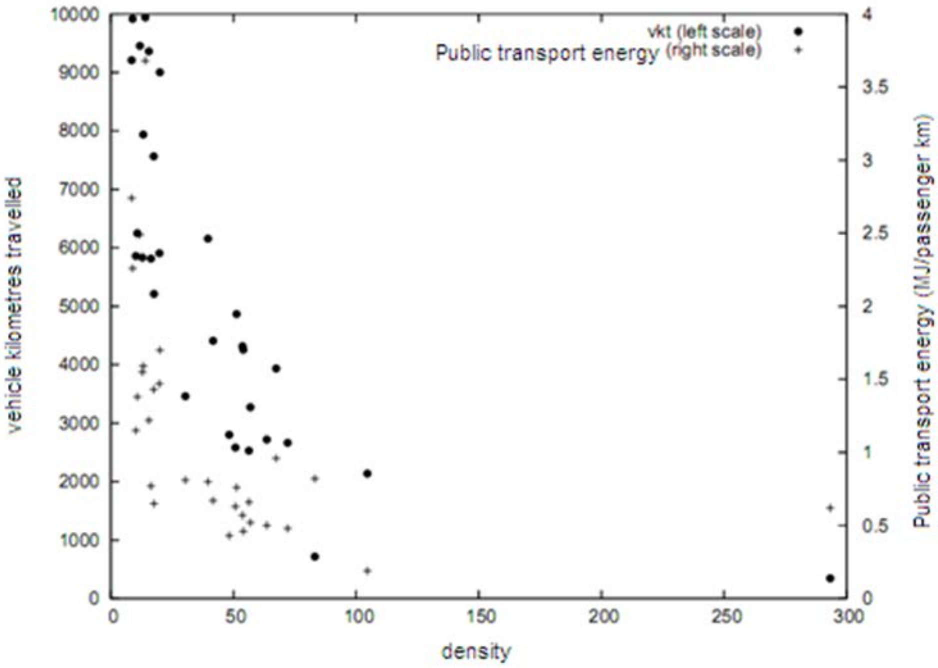


Figure 2.4. Urban density, private VKT, and public transport energy consumption (MJ/passenger-km) outcomes (Newman et al. 1989)

There are various schools of thoughts both for and against Newman and Kenworthy's opinion about the effects of density on transport which are summarised as follows:

For: Density decreases energy consumption

Compact city theory was introduced in 1960s, which argues that higher urban population density is effective in terms of travel reduction. This theory claims that compact cities are more sustainable with regards to transport energy consumption and emissions. The reason is that in denser areas, people are nearer to public transport and they also prefer to use public transport more because of expensive parking and high congestion in high-density areas (Breheny 1995). Holden and Norland's (2005) research supported the theory of a compact city as a sustainable urban form. They argued that everyday travel decreases in high-density areas. Banister et al. (1997) and Cervero (1996) also supported the idea of Newman and Kenworthy. Banister et al. (1997) analysed the energy efficiency of six urban settlements with different sizes in the UK and the Netherlands and found that higher density can lead to energy consumption reduction, while Cervero (1996) found that in 11 American cities higher urban densities increase non-motorised commuting.

Against 1: Density does not reduce energy use

Gordon et al. (1989) criticised the conclusions of Newman and Kenworthy study (1989) and argued that commuting times are shorter in decentralised cities because there is a considerable amount of commuting that take place between and within suburbs, which reduces congestion on roads leading to the city centre. They proposed the development of multi-centre cities and the implementation of a fuel tax as more effective strategies for reducing travel compared to population density. The study by Camagni et al. (2002) is another research contrasted with the compact city theory. They considered social and environmental costs of different urban expansion patterns and concluded that travel time by private transport is not strongly related to density or compactness of development, because increasing density causes shorter distances as well as greater congestion.

Against 2: Density may matter, but there are other factors

Although there are various researches which support a strong inverse relationship between population density and transport energy, some researchers believe that the real world is much more complex and there are many variables that effect travel behaviour. These researchers criticised Newman and Kenworthy (1989) by arguing that models which suggest compactness, simplify complex travel behaviour (Breheny 1992; Rickwood et al. 2008) and there is a need for more sophisticated measures of urban structure such as distance from CBD (Giuliano et al. 2006; Lindsey et al. 2011; Soltani & Somenahalli 2005), land-use mix (Soltani & Allan 2005; Zhang et al. 2006), dwelling types (Hess et al. 2002; Soltani & Allan 2005), and land consumption for transport infrastructure (Alford et al. 2008; Giuliano et al. 2006).

Dieleman et al. (2002) mentioned that the relationship between urban form and travel behaviour is extremely complex. Different features of the built environment, such as density, city size and urban structure have a composite impact on travel behaviour. Besides urban density, the diversity in land use may affect travel demand. A mixture of land uses could provide residents the opportunity to live and work within their own community. This leads to shorter travel distances and consequently can reduce car use. Alford and Whiteman (2008) believed that land-use mix, location of employment, services and shopping, the extent of the city area, local accessibility to transport infrastructure, the frequency of public transport services, the affordability of public transport fares, levels of car ownership, the availability of parking can all influence travel patterns.

On the other hand, some studies considered the effects of socio-economic factors rather than land-use factors on travel behaviour. Gender is a significant factor on travel behaviour in many studies, with women more likely to have sustainable travel behaviours compared to men. For example, Boarnet et al. (1998) in a study in southern California claimed that the relationship between land-use factors and travel behaviour is statistically insignificant for non-work car trip; and socio-demographic factors such as gender and age are more significant statistically. Household composition and income are also found to have major influences on travel behaviour in a number of studies. For example, Ryley's (2005) study in Edinburgh showed that households with children are highly dependent on cars and do not often use bicycles. In another study, Dieleman et al. (2002) studied the effects of urban form, household attributes, and residential context on travel behaviour. They found that higher income households are more likely to own and use a car and families with children are more likely to use a car than one-person families.

The review presented above demonstrates that the relationship between urban form and travel behaviour is still ambiguous and there is not any agreement among experts on this issue. A number of models have been developed to estimate travel behaviour as a function of socio-economic and land-use factors. Detailed descriptions of these models and their limitations are provided in Section 2.4.2.

2.4. Measuring transport sustainability

In recent years the subject of sustainable mobility has become very popular. It is because of the numerous problems faced by modern societies like air pollution, noise, congestion, safety, security, rising costs, and travel delays (Awasthi et al. 2011). Because of the socio-economic benefits of transport, as well as its social and environmental adverse effects, different studies have been conducted to develop the concept of sustainable transport for balancing these two aspects. The goal of sustainable transport is to ensure that environmental, social, and economic aspects are considered in decisions affecting transportation activities (Janic 2006). Quantifying transport sustainability is a challenging and complex task for many reasons such as:

- the multidimensionality of transport systems, which shows numerous system components, factors, effects and interrelationship between effects;
- the complexity of arranging the sustainability targets due to the above-mentioned interrelationships between effects;
- the complexity of evaluating the effects of specific policy measures and technologies on sustainability (Janic 2006).

Although sustainable transport is not defined clearly, over the past two decades there has been a growing interest in developing methods to measure transport sustainability. There is no common understanding about what is to be measured in sustainable transport because it is a multidimensional issue and there are many components and factors involved in the performance of transport systems. Therefore, measuring sustainability as a multi-objective problem needs to consider a mix of environmental, social and economic aspects (Janic 2006; Tao et al. 2003). One standard method to reduce the complexity of measuring sustainability is the use of indicators (Doody et al. 2009). In the area of transport, as in many other fields, indicators play a useful role in highlighting problems, identifying trends, policy formulation and evaluation. To evaluate areas in terms of transport sustainability, it is necessary to build a composite index that considers different aspects of transport sustainability. To aggregate indicators into a single index, first the quantified indicators are normalised to convert them to numbers without scale. Then a composite index is built by adding normalised indicators and by regarding different weights for different indicators which show their importance in the final index (Haghshenas et al. 2012). So quantifying sustainable transportation can be considered in six steps as shown in Figure 2.5.

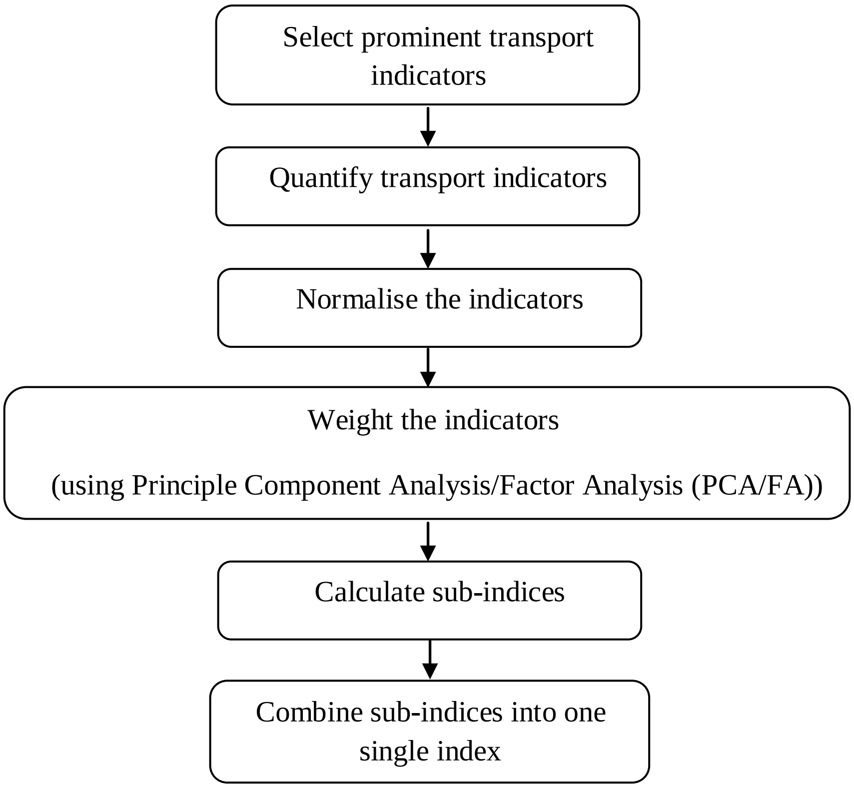


Figure 2.5. Process of developing transport sustainability index

2.4.1. Indicators selection

Sustainable indicators are variables that are used to measure progress towards sustainability. The development of sustainable indicators was first brought up at the United Nations Conference on Environment and Development (UNCED) held in Rio de Janeiro in 1992. Since then, indicators are used as important tools for measuring different aspects of sustainable development, including transport-related issues (Dobranskyte-Niskota et al. 2007). Indicators provide a high amount of information in a simple form that is easier to read and understand, so they facilitate communication among scientists, policymakers, and the public (Alberti 1996). They break down the complex concept into small and manageable units of information (Castillo et al. 2010). They can be used to evaluate the increasing or decreasing trends of various dimensions of sustainability. They also can provide information for decision makers to formulate planning strategies (OECD 2008). The attractiveness of indicators is related to their ability to show different dimensions of sustainable transport (Castillo et al. 2010). Figure 2.6 shows the position of an indicator in the hierarchy of sustainability concept.

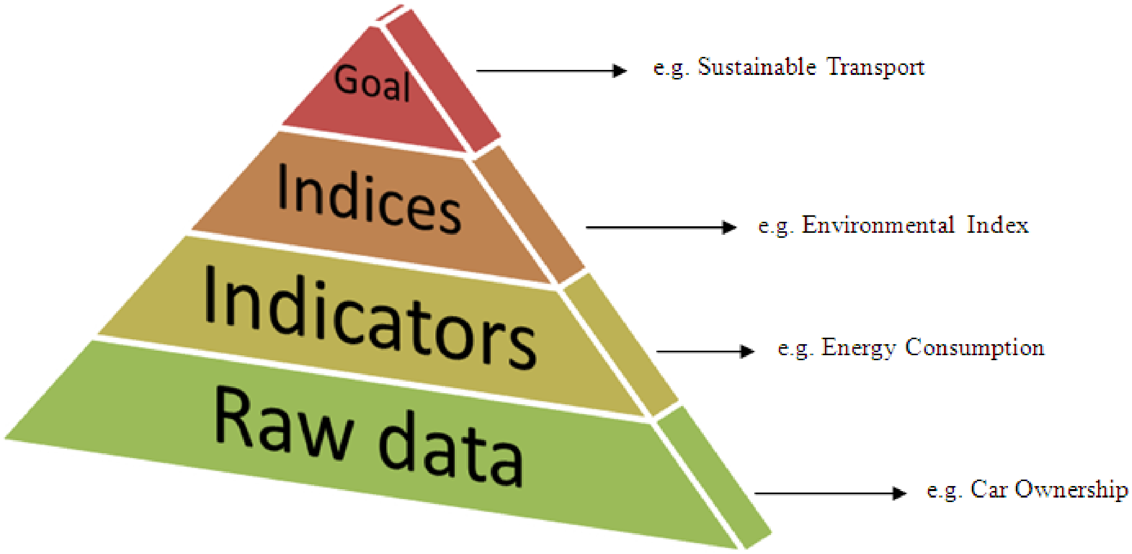


Figure 2.6. Hierarchy of sustainability concept (Zegras 2006)

The development of transport-specific indicators has been included in many recent studies. The indicators being used in those studies may be classified as one of the following: environmental, social, and economic. Table 2.1 lists the studies on sustainable transport indicators. The selection of a set of indicators that provides a holistic picture of the considered system is challenging (Castillo et al. 2010). It should be noted that indicators selection is primarily driven by the questions that indicators are supposed to answer. The quality of selected indicators is usually defined in terms of users' needs. Data that is produced too late, or are not easily accessible do not have good quality, even if they are accurate. Thus, quality is a multidimensional concept (OECD 2008). According to Haghshenas et al. (2012), indicators should be easily understandable, reasonable, measurable, possible to quantify, accessible, comprehensive, reflect various aspects of study, sensitive to changes over time, independent, clearly defined, and capture long-term processes. Although some studies such as Dobranskyte-Niskota et al. (2007) or Spiekermann et al. (2004) provide a long list of indicators, their selected indicators are not common among all transport sustainability studies. Table 2.2 presents the most common indicators considered in the studies presented in Table 2.1. As mentioned before, these indicators can be categorised in three main aspects: environmental, social, and economic. It is worth noting that indicators have been used to measure both determinants of sustainability and final outcomes. However, much of the literature does not distinguish between these two. For example, VKT is a determinant, while energy consumption and emissions are final outcomes.

Table 2.1. Studies on transport sustainable indicators

Title	Author (Year)	Number of proposed sustainable transport indicators
Towards an urban transport sustainability index: an European comparison	Zito and Salvo (2011)	32
ELASTIC- A methodological framework for identifying and selecting sustainable transport indicators	Castillo (2010)	20
Addressing sustainability in transport systems: definitions, indicators, and metrics	Jeon and Amekudzi (2005)	30
Urban sustainable transportation indicators for global comparison	Haghshenas and Vaziri (2012)	9
Sustainable transport indicators for Cape town, South Africa: Advocacy, negotiation and partnership in transport planning practice	Kane (2010)	18
Sustainable transportation indicators: A recommended research program for developing sustainable transport indicators and data	Litman (2009)	30
Evaluating urban sustainability using land-use transport interaction models	Spiekermann and Wegener (2004)	35
A GIS as a decision support system for planning sustainable mobility in a case study	D’Amico et al. (2012)	22
Multi-criteria sustainability evaluation of transport networks for selected European countries	Kolak et al. (2011)	17
Sustainable transportation performance indicators (STPI)	Gilbert et al. (2002)	14
Indicators to assess sustainability of transport activities	Dobranskyte-Niskota et al. (2007)	55
Towards sustainable mobility indicators: application to the Lyons conurbation	Nicolas et al. (2003)	21
Sustainable transport indicators and assessment methodologies	Zegras (2006)	7

Table 2.2. Sustainable transport indicators in Table 2.1 studies

Aspect	Indicators	Determinants
Environmental	GHG emission	• Vehicle kilometre travelled by car • Passenger kilometre travelled by public transport • Mode share
	Other air pollutants	• Vehicle kilometre travelled by car • Passenger kilometre travelled by public transport • Mode share
	Energy use	• Vehicle kilometre travelled by car • Passenger kilometre travelled by public transport • Mode share
	Population exposed to noise	• Traffic volume
	Land consumption for transport	• Land-use mix • Length of railways and main roads • Length of cycling and walking passes
Social	Fatality and injuries related to traffic accidents	• Vehicle ownership
	Accessibility to facilities and public transport	• Length of railways and main roads • Proportion of residents with public transit services within 500 m
	Satisfaction of citizens and variety and quality of transport options	• Quality of transport for disadvantaged, disabled, children, non-drivers • Quality of pedestrian and bicycle environment
	Fatality and injuries resulted from air pollutants	-
Economic	Household expenditure allocated to transport	• Costs of parking • Fuel price • Commute costs • Total time spent in traffic and congestion costs • Vehicle costs • Transport taxes and subsides
	Accident cost	-
	Transport emission costs	• Vehicle kilometre travelled by car • Modal split
	Noise costs	-

2.4.2. Quantifying environmental indicators

A large number of studies have tried to develop land-use/transport interaction models to estimate transport energy consumption and emissions as the important transport environmental indicators. The land-use/transport interaction models that have been developed in the last 20 years can be categorised in two general groups. These two groups show the tension between complexity and applicability. The more detailed and sophisticated a model, the less general it becomes, and the more difficult and time consuming it is to apply.

- Computational models: Most of these models are based on the four-step transport model which was first developed in 1950s (Davidson 2011; Newton 1997). The four-step transport model considers trip generation, trip distribution, modal choice, and route assignment (Davidson 2011). Examples of these models are ITLUP, MEPLAN, MUSSA, UrbanSim (Hunt et al. 2005). Most of these models are extremely complex and their running time is too long in the order of hour or even day (Davidson 2011; Webster et al. 1990). A detailed review of these models can be found in Hunt et al. (2005), Timmermans (2003) , and Wegener (1994).

- Statistical models: These simple models use multiple regression analysis to consider relationships between land-use and transport variables. Examples of these models are regression models of Naees (2009), Paravantis et al. (2007), and Giuliano et al. (2006). Another famous example of such statistical studies is that of Newman and Kenworthy (1989), who investigated the relationship between urban density and transport energy consumption in 32 cities all around the world. There is an argument that multiple regression analysis is not good enough for developing land-use/transport interaction models because of co-linearity problem among selected variables (Öğüt 2006). It is also argued that the relationship between dependant variables and independent variables varies in different parts of the city and there is a geographic variation for the relationship (Whelan et al. 2010), so this relationship cannot be modelled by multiple regression analysis.

One of the important aspects of land-use/transport interaction models is that, researchers who have developed these models, have restricted themselves to consider land-use/VKT models or land-use/car ownership models or land-use/modal split models, rather than an integrated model, which considers car ownership, modal spilt, and VKT at the same time. For example, Whelan et al. (2010) developed a model for car ownership estimation in London. They argued that household income, household type, population density, age, tenure, nationality, public transport accessibility, and ownership costs are factors that affect car ownership. Further in Sydney, Corpuz et al. (2006) developed a model to predict VKT, given a set of socio-economic, location, and urban form characteristics such as the number of vehicles in a household, closest distance to major centre or CBD, land-use mix, local employment, housing density, and distance to nearest public transport. Their model showed that the areas nearer to the CBD and those with higher densities generate lower VKT per household. In addition, there was a clear reduction in VKT generation in areas located close to public transport nodes. Another important aspect of land-use/transport interaction models is that most of the models are developed in one spatial scale (Giuliano et al. 2006; Lindsey et al. 2011; Næss 2009). Based on a comprehensive review by the author, there is only one study (Corpuz et al. 2006) in which a regression model was developed to quantify VKT as a function of some land-use variables at household, collection district (CD) and travel zone (TZ) levels. Their results showed that in a larger scale (TZ in this case), there is more apparent linear relationship between dependant and independent variables compare to other scales.

Based on the review presented above about land-use/transport interaction models, to cover the current gaps, this study tried to develop two statistical and one computational integrated land-use/transport models that consider land-use effects on car ownership, VKT, and modal split altogether, and then use them to quantify environmental indicators. The proposed models are very simple, do not employ complex mathematics and are easily understandable by policy makers. The results of different models were compared to evaluate their abilities in modelling land-use/transport interaction. Moreover, the models were developed in two different spatial scales, statistical local area (SLA) and census collection district (CCD), to investigate the spatial transferability of developed land-use/transport interaction models.

2.4.3. Quantifying social indicators

Although a large number of studies try to identify social indicators, relatively little research has been done in developing methods for estimating transport social impacts. Because of the different forms of transport social impacts, some of them may be difficult to estimate (Forkenbrock et al. 2001). Most of the studies on social effects of transport are focused on fatalities and injuries related to air pollutants and crashes. For example, in the US, Ozkaynak et al. (1987) examined 100 metropolitan areas using the 1980 vital statistics. They found statistically significant relationships between mortality rates and ambient particulate matters including sulphates and fine particulates. In traffic accidents studies, ARRB (2007) tried to quantify crash rates for Australian roads using crash data from road authorities or in another study, Wang et al. (1999) tried to quantify crash rate for different type of vehicles.

In terms of measuring accessibility as one of the important social indicators, most of available research have measured accessibility to a particular facility such as hospitals (Apparicio et al. 2008; Khan 1992; Wang et al. 2005) or parks (Maroko et al. 2009; Zhang et al. 2011). Moreover, some others consider accessibility for special groups of people such as parents and caregivers of young children (Witten et al. 2003). There are few studies that consider a different range of facilities for the whole population (Lotfi et al. 2009; Pitot et al.

2006). There are also some attempts to quantify accessibility in Australia. One of the early attempts to develop an index of accessibility for non-metropolitan Australia was that of Faulkner and French (1983) . They created a grid map over Australia with 702 squares and then measured the distance from the centre of each square to the nearest urban centre. These distances were combined into a single number and normalised using z-scores to obtain relative accessibility. Another major attempt to generate an index of accessibility was the RRMA, carried out by the Department of Primary Industries and Energy and Department of Human Services and Health (1997). An index of accessibility was calculated for each SLA in a similar way to the Faulkner and French approach. These two studies are criticised because of measuring straight-line distance, which does not capture all dimensions of accessibility. A better approach was taken by the National Centre for Social Applications of GIS (GISCA) at the University of Adelaide to develop Metropolitan Accessibility/Remoteness Index of Australia (ARIA). It quantifies levels of accessibility by measuring the road distances people travel from their home to reach health, shopping, education, public transport, financial, and postal services and then combined them to produce the final Metro ARIA. A weakness of the Metro ARIA approach is that it considered public transport solely as a service to be accessed, and not as a means of potential access.

To sum up, although there are some attempts to quantify social impacts of transport, there is no comprehensive study tries to quantify sustainable transport social indicators and develop an index for social transport sustainability. Moreover, based on available accessibility indices for Australia, there is a need for a comprehensive accessibility index for walking and public transport in Melbourne. To fill these gaps, this study tried to quantify different social indicators and develop an index for social sustainable transport. An accessibility index was also developed to quantify accessibility by walking and public transport to different facilities in Melbourne.

2.4.4. Quantifying economic indicators

Economic analysis is a way for considering cost effectiveness of an option compared to others, and find out which option provides the greatest benefits (Litman 2009). Although transport has positive impacts such as effects on the growth of the national economy and satisfying people’s mobility needs, it has adverse effects such as accidents, noise, air pollution, harm to health, crops damage, and traffic jams (Kunzli et al. 1999). These impacts cause large costs, which are estimated to be about 5% of GDP for industrialised countries (Nijkamp et al. 2011). As these costs are excluded from the market price, motorists’ behaviours are not based on these costs. If these costs were included, trips may cost more, many trips would be avoided and resources conserved (Kunzli et al. 1999).

Despite large number of studies list economic indicators (Dobranskyte-Niskota et al. 2007; Gilbert et al. 2002; Jeon et al. 2005; Litman 2003; Nicolas et al. 2003), fewer studies try to quantify different range of transport costs. For example, Litman (2003) presented a long list of 16 transport costs and quantified them all. Levinson et al. (1998) (Levinson et al. 1998) also developed a full cost model that identified user costs, infrastructure costs, time and congestion costs, noise costs, accident costs, and pollution costs. Most of available studies limit their scope to just one cost that can be related to transport. For example, McCubbin et al. (1999), Kunzli et al (1999), and Chestnut et al. (1994) estimated the health costs of transport air pollution. Indeed, Deluchi et al. (1998) tried to quantify damage cost of transport noise; Connelly et al. (2006) and Miller (1993) tried to quantify economic costs of road traffic accidents. Based on my knowledge, there is no study that integrates transport economic indicators into a single index, which is a major gap in transport economic studies.

To sum up, there is a lack of study in quantifying a varying range of economic indicators and development of an index for sustainable transport from an economic aspect. This study tried to fill this gap by quantifying different ranges of economic indicators and developed an economic sustainability index for transport.

2.4.5. Normalising transport indicators

Transport indicators contain different types of information so there is inconsistency in units among indicators. Therefore, before indicators aggregation, it is necessary to transform them to numbers without any dimension. This process is called normalisation (Nardo et al. 2005). There are different normalisation techniques which are summarised in Table 2.3. The selection of appropriate normalisation method depends on properties of available data and the objectives of final composite index (Freudenberg 2003). The selected normalisation method for this study and the reason for the selection will be presented in Chapter 5.

Table 2.3. Summary of normalisation methods (Nardo et al. 2005; OECD 2008)

Method	Equation
Ranking	$I_{qc}^{t} = Rank(x_{qc}^{t})$
Z-score	$I_{qc}^{t} = \dfrac{x_{qc}^{t} - x_{qc=\bar{c}}^{t}}{\sigma_{qc=\bar{c}}^{t}}$
Re-scaling	$I_{qc}^{t} = \dfrac{x_{qc}^{t} - \min_{c}(x_{q}^{t})}{\max_{c}(x_{q}^{t}) - \min_{c}(x_{q}^{t})}$
Distance to reference	$I_{qc}^{t} = \dfrac{x_{qc}^{t}}{x_{qc}^{t_{\underline{0}}}}$ or $I_{qc}^{t} = \dfrac{x_{qc}^{t} - x_{qc}^{t_{\underline{0}}}}{x_{qc}^{t_{\underline{0}}}}$
Logarithmic transformation	$I_{qc}^{t} = \ln(x_{qc}^{t})$
Categorical scale	If x_{qc}^{t} is in the upper 5-th percentile then I_{qc}^{t} =100 If x_{qc}^{t} is in the upper 5-15-th percentile then I_{qc}^{t} =80 If x_{qc}^{t} is in the upper 15-35-th percentile then I_{qc}^{t} =60 …..
Indicators above and below the mean	if $\dfrac{x_{qc}^{t}}{x_{qc}^{t_{\underline{0}}}} > (1+p)$ then $I_{qc}^{t} = 1$ if $\dfrac{x_{qc}^{t}}{x_{qc}^{t_{\underline{0}}}} < (1-p)$ then $I_{qc}^{t} = -1$ if $(1-p) < \dfrac{x_{qc}^{t}}{x_{qc}^{t_{\underline{0}}}} < (1+p)$ then $I_{qc}^{t} = 0$
Cyclical indicator	$I_{qc}^{t} = \dfrac{x_{qc}^{t} - E_{t}(x_{qc}^{t})}{E_{t}(\lvert x_{qc}^{t} - E_{t}(x_{qc}^{t})\rvert)}$
Percentage of annual difference over consecutive years	$I_{qc}^{t} = \dfrac{x_{qc}^{t} - x_{qc}^{t-1}}{x_{qc}^{t}}$
$Rank$ = Rank indicator across areas x_{qc}^{t} = Indicator q for area c at time t	

I_{qc}^{t} = Normalized indicator q for area c at time t

$x_{qc=\bar{c}}^{t}$ = Average of indicator q across areas

$\sigma_{qc=\bar{c}}^{t}$ = Standard deviation of indicator q across areas

$\max_c(x_q^t)$ = Maximum of x_q^t across areas

$\min_c(x_q^t)$ = Minimum of x_q^t acroos areas

$x_{\bar{qc}}^{t_0}$ = Indicator q for refrence area at time t_0

p = An arbitrary threshold around mean

$E_t(x_{qc}^t)$ = Indicator's mean over time

2.4.6. Weighting indicators

Indicators that are aggregated into a composite index must be weighted before aggregation (Freudenberg 2003). This step is used to attribute a value to one indicator compared to others (Tanguay et al. 2010). All indicators may be given equal weights or different weights, which reflect the significance of indicators. The weights given to different indicators influence the final composite index (Freudenberg 2003). Weighing is also done for overlap correction among correlated indicators to ensure unbiased results (Dur et al. 2010). Weighing methods can be classified in three categories:

- **Equal weighting:** In this method, all indicators are given the same weight, which implies that each indicator has the same impact on the final index. If two or more indicators are correlated, there is a risk of double counting in this method (Freudenberg 2003). This method is often used because of its simplicity (Saisana 2011).

- **Weighting based on statistical analysis:** Principal component analysis/factor analysis (PCA/FA), data envelopment analysis (DEA), and benefit of the doubt belong to this category. Weights based on PCA/FA consider correlation among indicators to form a composite index that captures the information of individual indicators as much as possible (OECD 2008; Saisana 2011). DEA, developed by Charnes et al. (1978), is a non-parametric technique that is used for evaluation of efficiencies in decision-making units (DMUs) using some specific mathematical programming models. In DEA, each DMU selects a set of weights that are most favourable for having a higher efficiency score. In other word, a DMU attaches less importance to those dimensions on which it is weak compared to other DMUs in the set (Kao et al. 2005), so it always overestimates efficiency. However, the extent of the overestimation is highly dependent on sample size. When the sample size is relatively small, we expect a large number of DMUs to be assessed as DEA-efficient (Chaparro et al. 1997).The application of DEA to the field of composite indices is known as the 'benefit of the doubt' approach and was proposed to evaluate macroeconomic performance. In this method, composite index is used to compare an area relative to other areas in the set or to some external benchmarks (Cherchye et al. 2007). Composite index is not calculated by a weighted sum of its indicators, but rather by the ratio of this sum to a weighted sum of the benchmark indicators. So, a value of 100% implies a performance that is similar to the benchmark value and a value less than 100% refers to worse performance (OECD 2008).

- **Weighting based on opinions:** The most common method in this category is the analytical hierarchy processes (AHP). AHP is a widely used technique for multi-attribute decision making. It disaggregates a problem into a hierarchical structure in which both qualitative and quantitative aspects of a problem are evaluated using pair-wise comparisons. Pair-wise comparisons are made between pairs of indicators, asking experts which of the two indicators is more important, and by how much. The preference is expressed on a scale of 1 to 9, where 1 indicates equal importance between two indicators, while 9 indicates that one indicator is nine times more important than another. People's opinions are not always consistent. AHP has the ability to check consistency of the comparison matrix. Weights of indicators in AHP method represent the trade-off across indicators and they are not importance coefficients. So it could cause misunderstandings if AHP weights be interpreted as importance coefficients (OECD 2008). This method is recommended for less than 10 indicators, and is not transferable from one area to another (Saisana 2011).

Available research mostly used equal weighting and AHP for indicators weighting. For example, Campos et al. (2008) used a group of specialists' ideas to weight sustainable mobility indicators based on the AHP process. In another study in UK, Castillo et al. (2010) used AHP to weight sustainable transport indicators based on transport planners and academics opinions. Tao et al. (2003) in considering sustainable transport indicators using AHP, found that based on experts' opinions, environmental indicators have the highest weight compared to other indicators. In another study, although Rossi et al. (2013) suggested a new approach for evaluating transport sustainability by applying Fuzzy logics, they use experts' judgements for weighting indicators. Despite its wide use, AHP might not be a good method because it is subjective and there might be inconsistency between experts’ opinions (OECD 2008; Saisana 2011). In contrast, Haghshenas et al. (2012) took a simpler approach and gave the same weights (1) to all environmental, social, and economic indicators. Equal weighting leads to biased results as different indicators have different importance in the final index. In conclusion, there is a need for a better weighting method that is not subjective and considers differences among indicators. So, this study tried to take the best approach for weighting sustainable transport indicators.

2.4.7. Development of sub-indices and a single transport sustainability index

Aggregating individual indicators into a composite index is a practical approach for sustainability evaluation (Dur et al. 2010). A composite index is a mathematical aggregation of individual indicators that measures different aspects of sustainability that cannot be captured completely by individual indicators alone (Nardo et al. 2005; Saisana 2011). The main characteristic of the indices is that they do not have units, so that they are considered neutral and comparison between them is possible (Dur et al. 2010). Advantages and disadvantages of a composite index are provided in Table 2.4. Despite their shortages, composite indices are in use due to their usefulness as a communication tool (Freudenberg 2003). There are two conflicting views about composite indices. The opponents of composite index believe that composite index is not reliable because its construction is subjective (Cherchye et al. 2007). No single index can answer all questions and there is a need for multiple indicators (Jollands et al. 2003). Moreover, aggregation of the indicators into a single index makes it difficult to identify negative or positive changes in the indicator due to the offsetting effects of positive indicators on negative ones (Dur et al. 2010). Lack of a standard construction methodology, and particularly the subjectivity in indices’ construction, are elements that are used by opponents to undermine their credibility (Cherchye et al. 2007). On the other hand, some researchers believe that composite indices are valuable communication tools because they limit the number of presented information and allow for quick and easy comparisons (Freudenberg 2003). It is often easier for the general public to interpret composite indicators than to identify common trends across many separate indicators (OECD 2008). These two ideas are two sides of the coin and it can be concluded that indicators aggregation is successful if clear assumptions and methodology are used and if the index can be disaggregated into its components (Jollands et al. 2003).

Although many attempts were done to identify sustainable transport indicators (Table 2.1), limited number of studies aggregate different indicators into a single index. D'Amico et al. (2012) integrated 22 indicators in environmental, social, and economic aspects using budget allocation for weighting to find a sustainable mobility index for the district of Naples. They claimed that the developed index can show the trend towards sustainable mobility and it is a powerful tool to support decisions. Zito et al. (2011) in developing transport sustainability index considering environmental, social, and economic aspects argued that all aspects have an equal relevance for measuring progress towards a sustainable transport and giving different weights to each aspect does not make sense. Haghshenas et al. (2012) integrated three environmental, three economic, and three social transport indicators into a single composite index. They used z-scores to normalise indicators and then considered similar weights for each aspect. Normalised indicators were aggregated using an additive weighted method. These studies used statistical data and survey results for indicators quantification and they developed transport sustainability index for the present condition of countries. There is a lack of study that develops models for indicators quantification and develops a transport sustainability index for the future under different scenarios. This study tried to fill these gaps by quantifying environmental, social, and economic indicators using a land-use/transport interaction model, and by developing a transport sustainability index for Melbourne 2030 under different urban-planning scenarios.

Table 2.4. Advantages and disadvantages of a composite index (OECD 2008)

Advantages	Disadvantages
• can summarise complex, multi-dimensional information to support decision makers • are easier to interpret than many single indicators • reduce the size of a set of indicators without eliminating the basic information • can assess progress of area over time • facilitates communication with public • enables users to compare complex dimensions effectively	• may send misleading message if poorly constructed or misinterpreted • may cause simplistic conclusion • The selection of indicators and weights is a matter of concern • may be misused to support a desired policy if the construction process is not clear

2.5. Conclusions

Based on the literature reviewed, it can be concluded that there are three major gaps in the current pool of knowledge. There is a:

- lack of an integrated land-use/transport interaction model which considers car ownership, VKT, and mode share altogether that is easy to use and understand by policymakers;

- lack of consideration of the effect of spatial scale on land-use/transport interaction modelling;

- lack of sustainable transport indices for assessing different urban-planning strategies over time with better weighting and aggregation methods.

In order to fill the current knowledge gaps, this study:

- developed a land-use/transport integrated model for estimating transport energy consumption and emissions. The integrated model contains three sub-models: car ownership, VKT, and modal spilt. This model was developed in two spatial scales (SLA, CCD) to examine spatial transferability of developed modelling techniques over different spatial scale.

- developed three indices, transportation environmental impact index (TEII), transportation social impact index (TSII), transportation economic impact index (TCII) and finally the composite sustainable transport index for different urban-planning strategies for future Melbourne, using the results of an integrated land-use/transport interaction model as one of the major inputs.

Chapter 3 considered different techniques for land-use/transport interaction modelling. After quantifying car ownership, VKT, and modal split, transport sustainability environmental indicators were selected and quantified in the next chapter.

Chapter 3

Environmental Indicators

3.1. Introduction

Sustainable development comprises environmental, social and economic aspects. One of the objectives of this thesis is to develop environmental, social, and economic indices for sustainable transport. In this chapter the values of environmental indicators were quantified using land-use/transport model. While in the next chapter, social and economic indicators will be quantified. This chapter has two sections. First, environmental indicators are selected and discussed and second the integrated land-use/transport models are developed to quantify the selected environmental indicators. Social and economic indicators and their quantification will be discussed in the next chapter.

3.2. Transport environmental indicators

Decision makers need to consider a large number of negative impacts related to transport activities, while trying to achieve sustainable transport systems. Developing indicators for transport plays a major role in the decision-making process for sustainable transport. Indicators play a useful role in highlighting problems, identifying trends, policy formulation, and evaluation (Dobranskyte-Niskota et al. 2007). In most cases, one single indicator is not adequate, and a set of indicators that reflects various impacts should be used. Currently a large number of international studies develop transport-specific indicators. Moreover, a number of international organisations have tried to develop indicators to achieve a more sustainable transport on the local, regional, and global levels. Differences in the selected indicators are due to mission and policy priorities in different organisations (Dobranskyte-Niskota et al. 2007). Transport-related environmental indicators which appeared most frequently in the literature are provided in Table 3.1.

Selecting a set of indicators that provides a holistic picture of the considered system is challenging (Castillo et al. 2010). Choosing indicators often involves tradeoffs. While using a smaller set of indicators is more convenient, it may overlook the important impacts. On the other hand, a large set of indicators is comprehensive but its collection and analyses costs are extensive. So some criteria are needed for indicators selection. Some selection criteria were used to identify a list of indicators that could be used to measure transport sustainability in Melbourne (Table 3.2).

Table 3.1. Transport environmental indicators

Environmental Indicator	Frequency of use	References
GHG emission	13	Zito and Salvo (2011), Castillo and Pitfield (2010), D'Amico et al. (2012), Dobranskyte-Niskota et al. (2007), Gilbert et al. (2002), Jeon and Amekudzi (2005), Kane (2010), Kolak et al. (2011), Litman (2009), Nicolas et al. (2003), Spiekermann and Wegener (2004), Zegras (2006), Haghshenas and Vaziri (2012)
Energy use	9	Castillo and Pitfield (2010), Dobranskyte-Niskota et al. (2007), Gilbert et al. (2002), Haghshenas and Vaziri (2012), Jeon and Amekudzi (2005), Kane (2010), Litman (2009), Nicolas et al. (2003), Spiekermann and Wegener (2004)
Other air pollutants	9	Castillo and Pitfield (2010),D'Amico et al. (2012), Dobranskyte-Niskota et al. (2007), Gilbert et al. (2002), Haghshenas and Vaziri (2012), Jeon and Amekudzi (2005), Litman (2009), Nicolas et al. (2003), Spiekermann and Wegener (2004)
Population exposed to noise	8	D'Amico et al. (2012), Dobranskyte-Niskota et al. (2007), Haghshenas and Vaziri (2012), Jeon and Amekudzi (2005), Litman (2009), Nicolas et al. (2003), Spiekermann and Wegener (2004), Zegras (2006)
Land consumption for transport	4	Haghshenas and Vaziri (2012), Jeon and Amekudzi (2005), Nicolas et al. (2003), Spiekermann and Wegener (2004)
Vehicle kilometer travelled	4	Jeon and Amekudzi (2005), Litman (2009), Zito and Salvo (2011), Nicolas et al. (2003)
Length of railways and main roads	2	Jeon and Amekudzi (2005), Gilbert et al. (2002)

Table 3.2. Criteria for indicators selection

Criteria	Description	References
Relevance	Each indicator must properly embrace the definition and theoretical basis of sustainability	Dur et al. (2010)
Representative and comprehensive	Selected indicators should address environmental, social and/or economic aspects of transport	Dur et al. (2010), Li et al. (2009), Spiekermann and Wegener (2004), Zito and Salvo (2011)
Data availability	Needed data must be available easily and at a reasonable cost	Haghshenas and Vaziri (2012), Zito and Salvo (2011)
Quantifiable	Indicators must be quantifiable	Li et al. (2009)
Understandable by users	Indicators must be simple	Haghshenas and Vaziri (2012), Zito and Salvo (2011)
Independent	Indicators should be independent of each other	Haghshenas and Vaziri (2012), Li et al. (2009)
Predictability	As indicators usually are used to model future policy impacts, it is essential that indicators values can be forecasted for the future	Dur et al. (2010), Spiekermann and Wegener (2004)

Screening by the selection criteria, only a small number of environmental indicators were found suitable for the study area (Table 3.3). A selected spatial scale for this study, SLA, restricted the number of evaluated indicators that can be quantified using available data. Some indicators such as VKT, and length of railways and main roads were not directly considered as an indicator, but rather they were used to quantify selected indicators such as depletion of non-renewable resources and emissions.

Table 3.3. Selected environmental indicators for Melbourne

Selected indicators for the study	Unit
Depletion of non-renewable resources	Litres of crude oil per household annually
GHG emissions ($CO_{2\text{-}e}$)	kilograms per household annually
Other air pollutants (CO, PM_{10}, NO_X)	kilograms per household annually
Land consumption for transport	km^2 per household

The inclusion of depletion of non-renewable resources is justified by the definition of a sustainable transport system as the system that minimises non-renewable resources consumption. According to another definition of sustainable transport, as one that produces emissions only within the planet's ability to absorb them, selection of GHG emissions as one of the transport environmental indicators is justifiable. GHG emissions from transport are almost correlated with fossil fuel use and consequently depletion of non-renewable resources. The close matching of these two indicators raises the question as to why both have been chosen. Both have been chosen because of separate important impacts in relation to resources depletion and global warming. Emissions of pollutants rather than GHGs into air from transport are major sources of poor air quality. The justification for including them is the same as that for greenhouse gas emissions.

3.3. Quantifying environmental indicators

After selecting indicators, values must be assigned to different indicators, so indicators must be quantified. For this study, the databases applied were 2006 ABS database and Victorian Integrated Survey of Travel and Activity 2007 (VISTA07). Using these databases, the values of effective factors on travel behavior such as population density, dwelling types, household types, and household income were extracted. These valued were used to quantify transport sustainability determinants (i.e. VKT, percentage of trips by public transport) and consequently transport sustainability indicators.

3.3.1. Depletion of non-renewable resources

Transport fossil fuel usage causes the depletion of non-renewable resources and pollutions (OECD 1996). In this study, the amount of primary fuel (crude oil) consumed is a measure for resource depletion. To calculate the primary fuel consumed, first transport energy consumption is calculated using vehicle kilometer travelled (VKT) for private car, passenger kilometer travelled (PKT) for public transport, and an energy factor for private and public transport (Equation 3.1) (Rickwood 2009).

$$\text{Energy} = VKT_c * EnF_c + PKT_p * EnF_p \qquad 3.1$$

VKT_c = Vehicle kilometer travelled by private car

EnF_c = Energy factor for private car (4.6 MJ/VKT)

PKT_p = Passenger kilometer travelled by public transport

EnF_p = Energy factor for public transport (1.4 MJ/PKT)

To convert MJ of energy consumption in transport to litres of primary fuel, petroleum refinery efficiency must be calculated. In this study, petroleum refinery efficiency was calculated using Equation 3.2 (Wang 2008).Volumes and energy contents of petroleum refinery input and products in Melbourne available in Australian Government (2010) and BREE (2010) were used:

$$\text{Petroleum refinary efficiency} = \frac{\text{Energy content of all petroleum products}}{\text{Energy content of crude oil input}} \qquad 3.2$$

By knowing transport energy consumption and petroleum refinery efficiency in Melbourne (90%), litres of primary fuel consumed were calculated. The process of estimating petroleum refinery efficiency is presented in Appendix 1.

3.3.2. GHG emissions

This indicator was included because motor vehicles produce about one-fifth of man-made GHG emissions to the atmosphere. This indicator was calculated using GHG emission factors (Equation 3.3) (Rickwood 2009).

$$\text{GHG emissions} = VKT_c * EF_c + PKT_p * EF_p \qquad 3.3$$

VKT_c = Vehicle kilometer travelled by private car

EF_c = Emission factor for private car (0.26 kg $CO_{2\text{-e}}$/VKT)

PKT_p = Passenger kilometer travelled by public transport

EF_p = Emission factor for public transport (0.095 kg $CO_{2\text{-e}}$/PKT)

3.3.3. Emission of other air pollutants

Emissions of other air pollutants were also calculated using emission factors of selected air pollutants (Table 3.4). It is worth noting that emission factors for public transport are for buses. To estimate, emission factors for trams and trains, it was assumed that energy consumption in trains and trams are 72% of buses (Legacy et al. 2007). Moreover, to convert emission factor to kg/PKT, it was assumed buses, trams, and trains have 55, 210 and 1800 capacity, respectively (Carey 2013; Dowling 2013; Sydneybuses 2014).

Table 3.4. Emission factors for public and private transport (NPi 2002, 2008)

Pollutant	Emission factor for public transport	Emission factor for private transport
CO	5.06×10^{-3} kg/VKT	4.440×10^{-3} kg / VKT
PM_{10}	0.569×10^{-3} kg/VKT	8.030×10^{-6} kg /VKT
NO_x	10×10^{-3} kg/VKT	0.800×10^{-3} kg/VKT

So for measuring resources depletion and pollutants emissions from transport, VKT and PKT must be calculated. This thesis tried to consider different models to estimate VKT and PKT based on land-use/transport model.

3.3.4. Land consumption by transport

Areas of lands devoted to roads were measured using a Melbourne land-use map. In total, around 170 km^2 in 2006 was devoted to roads in Melbourne (see '2006\environmental indicators\land consumption for roads 2006.xlsx in Appendix 3). Figure 3.1 provides land area used for roads in each SLA in Melbourne 2006.

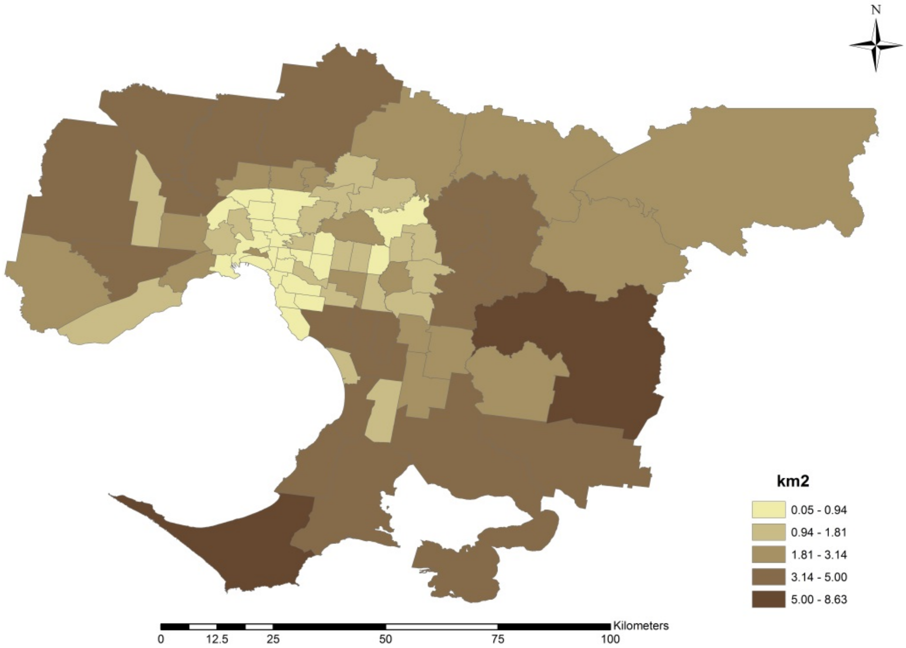


Figure 3.1. Land consumption for roads (Melbourne, 2006)

3.4. Land-use/transport interaction model for quantifying environmental indicators

3.4.1. Modelling the impact of land-use planning policy on travel behaviour

The view that physical planning can help achieve more sustainable consumption pattern has received considerable attention since 1987, following the Brundtland report (Holden et al. 2005). As mentioned earlier in Chapter 2, there are two general approaches for modelling the impact of urban planning on transport: statistical and computational. Statistical or analytical models identified mathematical relationship between variables and usually consider a small number of factors that influence transport. Well known examples of statistical land-use/transport models include Dargay and Hanly (2003), Holden et al. (2005), Newman and Kenworthy (1991). For example, Rodriguez et al. (2006) performed a multivariate regression, which related per capita vehicle miles travelled to a number of demographic, economic, and policy variables for twenty-five US cities. Another example of such statistical works is Guiliano et al. (2006) which examined the relationship between daily travel patterns, car ownership and urban form in US and Great Britain. In short, although urban systems are too complex to analyse, simple statistical analyses can provide valuable insights about urban transport.

Growth in the computational power enables more complexity in land-use/transport modelling. Computational models that usually need a great amount of data are complex and difficult to interpret. History of transport/land-use computational models is provided in Wenger (1994) and Hunt et al. (2005). In these models analyses first started from an aggregate level, and then developed for finer scales such as household levels and individual trip/activity levels, which increase the complexity of these models (Rickwood 2009). A strong argument against complex computational models is that of their calibration and application. The more complex the model, the more data is required to calibrate the model. So, simpler models are more appropriate if the data available is limited.

Simple statistical models are easily understandable by public, while computational models are sophisticated to generate a rich set of outputs to facilitate decision-making processes. So an approach that best describes household travel behaviour at a statistical local area (SLA) level was undertaken, comparing two statistical and one computational modelling technique.

3.4.2. Modelling approach taken in the thesis

One of the land-use/transport models applied in this thesis is computational, while two others are statistical. The base year of the models is 2006. To be able to compare these models, the same inputs were used. Developed land-use/transport models have three sub-models that are required to be built separately. The first sub-model is a car-ownership model, as car ownership is known to influence travel decisions. The second sub-model gives an estimate of the number of kilometres travelled by cars. The final sub-model estimates percentage of trips by public transport. Finally these three sub-models were integrated to estimate the depletion of non-renewable resources and transport related emissions, as selected transport environmental indicators. To calibrate the models, the holdout method was applied. This method partitions the data into two subsets, the calibration sample and the validation (or holdout) sample. Models are estimated with the calibration sample and the prediction errors of the estimated models are compared using the validation sample (Blattberg et al. 2008). 15% of the data were selected as validation sample to calculate errors in this study, that is a default setting in Artificial Neural Network (ANN) model. To be able to compare the models, all selected models must have the same calibration and validation samples. To evaluate spatial transferability of the developed models over different spatial scale, modelling was repeated for CCD level and compared with the results of SLA level (see Appendix 2). However, SLA level was selected as a major spatial scale for this study, as the data was not available for all CCDs in Melbourne.

- ***Car ownership model***

  Car ownership is an important component of transport modelling because of its role in transportation and land-use planning (Hess et al. 2002). Rapid growth rate of car ownership during past decades has increased energy consumption and emissions (Kobos et al. 2003; Pongthanaisawan et al. 2010). So car dependency is a big challenge for sustainable cities (Soltani & Somenahalli 2005) and can be used for predicting transport demand, energy consumption and emissions (De Jong et al. 2004).

  Relatively simple mathematical/computer models were developed for car ownership. Since car ownership is related to socio-economic and urban-planning factors, lots of available models were developed based on this relationship (Table 3.5). One example of a car-ownership model is Soltani & Somenahalli (2005) model, which was developed to consider the effect of different socio-economic factors (household size, household type, household income) and urban structure (density, land-use mix, distance to work place, dwelling structure) on car ownership in Adelaide. They concluded that higher income, living in a separate house, having larger families and families with more children, and living in a greater distance from the CBD increases the likelihood of having more cars, while higher density and higher job-housing balance decreases the need for more car ownership. In another study in London, Whelan et al. (2010) developed a model based on S-shaped function and geographically weighted regression (GWR) for car ownership estimation. They identified household income, household type, population density, age, tenure, nationality, public transport accessibility, and ownership costs as influential factors on car ownership. In a comparative study between US and UK, Guiliano et al. (2006) found that car ownership is largely related to income. In considering household income, household composition, housing type, and population density as explanatory variables for their car ownership model, they concluded that the number of cars increases with the number of adults in the household. Having children increases car ownership only in the US. Living in higher density areas, in row/terraced houses and apartments and near public transport reduces car ownership. Finally, they argued that the difference between the US and UK is because of their differences in factors such as fuel price, transit quality and availability of public transport, and social and cultural differences that were not included in the model.

To select effective factors for car ownership model, the same selection criteria for indicators selection (Table 3.2) were used. Based on the selection criteria and cited effective factors on car ownership (Table 3.5), factors which are used to model car ownership in Melbourne are provided in Table 3.6.

Table 3.5. Cited effective factors for car ownership

	Factors	**References**
Socio-economic factors	Household income	Giuliano and Dargay (2006), Kobos et al. (2003), Paravantis and Georgakellos (2007), Pongthanaisawan and Sorapipatana (2010), Soltani and Somenahalli (2005), Whelan et al. (2010)
	Proportion of couples with children to other household types	Giuliano and Dargay (2006), Whelan et al. (2010), Soltani and Somenahalli (2005)
Land-use factors	Population density	Giuliano and Dargay (2006), Whelan et al. (2010)
	Access to public transport	Giuliano and Dargay (2006), Whelan et al. (2010), Soltani and Somenahalli (2005)
	Proportion of detached houses to other dwelling types	Giuliano and Dargay (2006), Soltani and Somenahalli (2005)
	Distance to the CBD	Soltani and Somenahalli (2005)
	Job-housing balance	Soltani and Somenahalli (2005)
	Dwelling density	Soltani and Somenahalli (2005)

Table 3.6. Selected factors for car ownership model

	Factor	**Measurement unit**
Socio-economic factors	Household annual income	$
	Proportion of couples with children to other household types	-
Land-use factors	Population density	person/ha
	Access to public transport	km
	Proportion of detached houses to other dwelling types	-
	Distance to the CBD	km
	Walkability	-

These factors were quantified as follows for Melbourne 2006:

- Household annual income: annual income per household.

- Proportion of couples with children to other household types: ratio of the number of couples with children to the number of other household types.

- Population density: population of SLA divided by area of each SLA.

- Access to public transport: distance between the centre of each SLA and public transport stations.

- Proportion of detached houses to other dwelling types: ratio of the number of detached houses to the number of other dwelling types.

- Distance to the CBD: distance between the centre of each SLA and the CBD

-Walkability: walkability is measured as the ability to reach facilities by walking. Details of walkability measure are provided in Chapter 4. In this study, points of origin are Melbourne census collection districts' (CCD) centres and points of destination include parks, education facilities, health services, public transport stations, and business zones. It is worth noting that considering SLAs as points of origin may give misleading results, as SLAs are normally large and accessibility is not the same for different parts of one SLA. To overcome this problem, accessibility was quantified at the CCD level, and then the results were aggregated to SLA. CCDs are small enough to provide representative accessibility measures. In order to estimate walkability, shortest network distance between origins and destinations were calculated, using ArcGIS 9.2 Network Analyst Extension, Melbourne's land-use map, and Melbourne's roads network. Network Analyst finds distance (m) between origins and destinations. Then SLAs were weighted for the level of walkability according to the calculated distance, using a fuzzy linear function. The fuzzy linear function applies a linear function between the user-specified minimum and maximum values. Anything below the minimum is assigned 1 and anything above the maximum is assigned 0 (ESRI 1999). This minimum and maximum values show appropriate and inappropriate distance to facilities. For example, it was assumed that places with less than 500 m from parks are appropriate (full fuzzy) and places with more than 1500 m from parks are inappropriate (fuzzy-less) and fuzzy linear function was assigned fuzziness between 500 m and 1500 m. Appropriate walking distance to facilities are shown in Table 3.7. Therefore, each SLA is scored from 0 to 1 based on its walking distance to different facilities.

Table 3.7. Appropriate walking distance to facilities (minimum and maximum values) (Pitot et al. 2006)

Facilities	Appropriate distances for accessibility by walking
Business centres	800-1600 m
Health centres	600-1200 m
Education centres	600-1200 m
Parks	500-1500 m
Public transport stations	300-1000 m for bus, 600-1200 m for train

- ***VKT model***

VKT is an appropriate variable that can be used to model travel demand and its related energy consumption (Miller et al. 1998). Various investigations were done previously on the effect of urban form and socio-economic factors on distance travelled. Considering socio-economic factors, some studies showed that travel is a positive function of income and presence of children in household (Dargay et al. 2003; Giuliano et al. 2006). Among land-use factors, population density and distance to CBD are considered in most VKT models. The results of these models showed that by increasing the distance to the CBD, VKT increases, while density increase causes VKT reduction (Corpuz et al. 2006; Dargay et al. 2003; Lindsey et al. 2011; Næss 2009). But Miller et al. (1998) had a different idea and argued that distance to the CBD is the single most important explanatory variable, explaining 41% of observed variance in VKT. Another major urban factor that is considered in different research is metropolitan size. There are two opposing ideas about the effect of urban size on VKT. Guiliano et al. (2006) believed that metropolitan size is a proxy for the number and distribution of available opportunities. Variety of goods and services increases with metro size, hence those who live in the largest areas may be inclined to travel greater distances to obtain unique products or services. While Dargay et al. (2003) found that the number of journeys decreases with urban size. According to Corpuz et al. (2006), VKT is a positive function of the number of vehicle in the household and distance to nearest public transport. The selection criteria (Table 3.2) were used for selecting socio-economic and land-use factors of VKT model (Table 3.8).

Table 3.8. Selected factors for VKT model

	Factor	Measurement unit
Socio-economic factors	Household annual income	$
	Proportion of couples with children to other households	-
Land-use factors	Population density	person/ha
	Access to public transport	km
	Distance to the CBD	km
	Walkability	-
	Car ownership	-
	Land area of SLA	km^2

- ***Percentage of trip by car***

By providing a range of facilities within walking distance, residents would be less reliant on private vehicles for their trips. This can lead to a lower impact on urban environment (McKibbin 2011). There are considerable surveys about the effects of socio-economic and land-use factors on travel behaviour. Newman et al. (1991) in considering transport behaviour in 32 cities of the world found that urban density is the main parameter that affects modal split. In US and Australian cities with low population and job density, there is a high reliance on private cars, while in Asian cities with high density, people rely more on public transport (Newman et al. 1991). Kitamura et al. (1997) in considering trip generation by mode in five selected neighborhoods in San Francisco Bay Area found that differences in travel cannot solely be explained by differences in demographic and socio-economic factors and land-use factors are significantly associated with trip generation by mode. They found household income and household size as effective socio-economic factors on modal split, while distance to nearest public transport station and population density are effective land-use factors on modal split. Dieleman et al. (2002) in considering effective factors on modal split in the Netherlands found that private car usage is greater for families than for households without children. The reverse is true about using public transport because travelling by car is more convenient than public transport for households with children. Area of the city is another factor that affects number of trips by private cars. Considering the effects of car ownership, household income, household type, household education, and residential environment on modal split, they found that having a car reduces the tendency to go to work by public transport and that car ownership is the most important factor on modal split among considered variables. Based on available literature and the selection criteria (Table 3.2), effective factors on mode choice are selected for this study (Table 3.9).

Table 3.9. Selected factors for percentage of trip by car

	Factor	Measurement unit
Socio-economic factors	Household annual income	$
	Proportion of couples with children to other households	-
Land-use factors	Population density	person/ha
	Access to public transport	km
	Walkability	-
	Car ownership	car per household
	Land area of SLA	km^2

In the model developed in this study, public transport was assumed to be a substitute for cars. However, the substitution is not one-for-one. It was assumed that total travel demand is estimated by the distance that a household would travel (as estimated by VKT model) if they had full car ownership (i.e. two cars per household). For car ownership levels below two, it was assumed that public transport substitutes for the gap between total travel demand (estimated VKT with full car ownership) and actual travel demand (estimated VKT with actual car ownership) (Equation 3.4, 3.5):

$$pjp = 100 - pjc - pja \qquad 3.4$$

pjp = percentage of trips by public transport
pjc = percentage of trips by car
pja = percentage of trips by active transport (walking and cycling)

$$PKT = \alpha \times pjp\,(VKT_2 - VKT) \qquad 3.5$$

PKT = passenger kilometer travelled by public transport
VKT_2 = estimated VKT for full (2 cars) ownership
VKT = estimated VKT for actual car ownership

'α'is a constant of proportionality calculated across all households to make sure that summing individual household passenger kilometres matches published aggregate figures. According to Rickwood (2009) the best value for α was found to be 2.4, which was used for this study.

3.5. Different modelling techniques

In the previous section, car ownership, VKT, modal split, and effective socio-economic and land-use factors on travel behavior were considered. In this section, different modelling techniques are used to quantify these travel behaviour measurements. Before using different modelling techniques, some correlation analyses were undertaken between car ownership, VKT, percentage of trips by car as travel behaviour measurements, and selected land-use and socio-economic factors (Table 3.10). The correlation coefficients, which range from -1 to +1, show the strength of association between selected socio-economic factors, land-use factors, and travel behaviour measurements. Higher correlation coefficients show stronger link between variables. The sign of the coefficient denotes the trend of impact; the positive coefficient means the travel behaviour measurement has the same trend as the selected socio-economic and land-use factors. The significant level is also provided in Table 3.10. Statistical significance is the probability that a relationship between factors is not likely due to just chance alone. Significant level usually set at 0.05 (5%) or 0.01 (1%). Significant level of 0.05 means that findings have 5% chance of not being true, or 95% chance of being true (see '2006\ regression model 2006\ whole data.sav, correlation.spv in Appendix 3). It is worth noting that the units of the factors used do not influence correlation coefficients. Moreover, considering different forms of dependent and independent variables showed that 'ln (VKT)', 'ln (modal split)' and square root of household annual income provided stronger correlation relationships. These transformed variables were used in the following analyses.

Table 3.10. Correlation among travel behaviour measurements, land-use and socio-economic factors in Melbourne (2006)

	Car ownership (-)	VKT (km)	Trips by car (%)
Household annual income ($)	0.33**	0.22*	0.74**
Proportion of couples with children to other household types	0.53**	0.50**	0.63**
Population density (person/ha)	-0.43**	-0.44**	-0.81**
Access to public transport (km)	0.30**	0.42**	0.23*
Proportion of detached houses to other dwelling types	0.40**	N/A	N/A
Distance to the CBD (km)	0.17	0.42**	N/A
Walkability	-0.40**	-0.49**	-0.74**
Car ownership (-)	1	0.54**	0.36**
Land area of SLA (km^2)	N/A	0.33**	0.39**
** Level of significance = 0.01, * Level of significance = 0.05			

The results of Table 3.10 can be summarized as follow:

- ***Car ownership***: With a negative correlation coefficient between car ownership and population density (-0.43), it implies that higher population density is associated with a lower car ownership level. The correlation coefficient of 0.40 shows significant and moderate correlation between car ownership and proportion of detached houses to other dwelling types. The correlation between car ownership and distance to the CBD is positive but the correlation is not significant. As shown in Table 3.10, among socio-economic factors, car ownership appeared to be influenced by proportion of couples with children to other household types and household annual income. It seems that having children in a household is correlated stronger with car ownership than having higher income (0.53 compared to 0.33).
- ***VKT***: As shown in Table 3.10, among all selected factors, the distance travelled depends mostly on car ownership and household type. VKT increases if the household own more cars, has a high-income level and has children. Land-use factors remain influential in distance travelled. There is a clear trend to shorter travelling distances among households who live close to the city centre and public transport stations, and in smaller SLAs (with correlation coefficients 0.42, 0.42, 0.33 respectively). It should be noted that although population density and distance from the CBD both have significant influence on VKT, they are also highly correlated to each other; so to solve co-linearity problem in the later models, distance from the CBD is used for the VKT model and

population density is used for the car ownership and modal split models (As mentioned earlier, correlation between car ownership and distance to the CBD is not significant. According to the literature distance to the CBD is not considered in modal split models (Dieleman et al. 2002; Kitamura et al. 1997).

- ***Percentage of trips by car:*** This factor is strongly related to population density, proportion of couples with children to other household types, household income, access to public transport, SLA area, walkability and car ownership as shown in Table 3.10. Households with more children, with higher annual income and lived further distance from public transport stations travel more trips by car than by public transport. Car ownership significantly increases the likelihood that the car rather than public transport is used for travel.

Based on the correlation coefficients (Table 3.10), car ownership, VKT and percentage of trips by car can be estimated as functions of land-use and socio-economic factors. Three different modelling techniques were attempted to estimate them based on land-use and socio-economic factors that have significant correlations with travel behaviour. The analyses showed that SLA level is desirable for describing household travel behaviour. So SLA level (used in this thesis) can represent travel behaviour, while it does not require a high volume of data and readily works with widely available census-style data.

3.5.1. Linear regression model

To see if a linear relationship is appropriate between selected socio-economic, land-use factors, and travel behaviour measurements, linear regression was used for developing the models. Different parameters were used to evaluate regression analysis. The signs of the coefficients denote the trend of impacts; the positive coefficient means the dependent variable has the same trend as the independent variable. Moreover, R^2 shows how well a regression model fits the data and how much of the variance in the dependent variable is explained by the combination of independent variables. The closer R^2 is to 1, the better the model fits. Significance level or p-value tests the null hypothesis that the regression coefficient is equal to zero (i.e. there is no relationship between dependent and independent variables). A low p-value (<0.05) indicates that the null hypothesis can be rejected. With a p-value of 5% (or 0.05) there is only a 5% chance that results would have come up by chance. Co-linearity refers to a condition in which dependencies among the independent variables and its effect is to invalidate some of the basic assumptions underlying their mathematical estimation. Variance inflation factor (VIF) quantifies the severity of co-linearity in regression analysis. A VIF larger than 2 shows co-linearity among independent variables. A widely accepted VIF threshold for highest co-linearity among independent variables is 5 (Habibpour Gatabi et al. 2010).

- ***Car ownership***

  Car ownership, as a dependent variable, was modelled using a linear function of selected land-use and socio-economic factors (Table 3.11). It is often difficult to recognise which of the independent variables is most influential in determining the value of the dependent variable, since the values of the regression coefficients depend on the choice of variables units. Standardisation of the coefficients is usually done to answer the question of which of the independent variables have a greater effect on the dependent variable in a multiple regression analysis, when the variables are in different units of measurement. In other words, standardise coefficients make comparisons easy among independent variables with different units of measurement (see '2006\ regression model-2006\ car ownership regression.spv, regression car ownership.xlsx in Appendix 3).

Table 3.11. Linear regression coefficients for car ownership in Melbourne (2006)

Independent variables	**Standardised coefficients**	**p-value**	**Variance inflation factor**
Constant (-)	-9.03	N/A	N/A
Household annual income ($)	0. 16	0.19	1.68
Proportion of couples with children to other household types (-)	0.43	0.00	2.20
Population density (person/ha)	-0.28	0.13	3.68
Access to public transport (km)	0.32	0.01	1.76
Proportion of detached houses to other dwelling types (-)	-0.20	0.31	4.36
Walkability (-)	0.05	0.82	5.88
Adjusted $R^2 = 0.40$			

- ***VKT***

  A linear regression model was used to estimate household VKT. Regression coefficients are presented in Table 3.12 (see '2006\ regression model-2006\ VKT regression.spv, lnVKT regression.xlsx' in Appendix 3).

Table 3.12. Linear regression coefficients for VKT in Melbourne (2006)

Independent variables	Standardised coefficients	p-value	Variance inflation factor
Constant (km)	7.61	N/A	N/A
Household annual income ($)	-0.05	0.64	1.67
Proportion of couples with children to other household types (-)	0.47	0.002	2.53
Access to public transport (km)	0.38	0.01	2.33
Distance to the CBD (km)	0.41	0.04	4.78
Walkability (-)	0.37	0.12	7.02
Car ownership (-)	0.27	0.04	1.98
Area of SLA (km^2)	-0.10	0.51	2.91
Adjusted R^2=0.46			

- ***Modal split (percentage of trips by car)***

  The dependent variable for this regression analysis is defined as the percentage of trips by car (Table 3.13) (see '2006\ regression model-2006\ modal split regression.spv, modal regression.xlsx' in Appendix 3).

Table 3.13. Linear regression coefficients for percentage of trips by car in Melbourne (2006)

Independent variables	Standardised coefficients	p-value	Variance inflation factor
Constant (%)	-11.65	N/A	N/A
Household annual income ($)	0.43	0.00	1.72
Proportion of couples with children to other household types (-)	0.20	0.03	2.33
Population density (person/ha)	-0.50	0.00	3.90
Access to public transport (km)	0.01	0.92	2.32
Walkability (-)	-0.16	0.23	5.35
Car ownership (-)	-0.18	0.02	1.90
Area of SLA (km^2)	-0.19	0.05	2.78
Adjusted R^2=0.79			

Some of the linear regression coefficients are conflicting with the results of correlations. For example, while area of SLA is positively correlated with VKT, the sign of regression coefficient in linear regression VKT model is negative. This is because of co-linearity among selected independent variables. The likely possibility is that there is some dependency among population density, distance from CBD, area of SLA, and walkability since each has a VIF value larger than 2.

One suitable strategy for solving co-linearity problem is using stepwise regression that removes independent variables one at a time automatically until the VIF values for the variables remaining are all acceptable (<2). The results of stepwise regression for car ownership, VKT, and modal split are shown in Tables 3.14, 3.15, 3.16 (see '2006\ regression model-2006\car ownership regression.spv, car ownership regression.xlsx, vktregression.spv, lnvkt regression.xlsx, modal split regression.spv, modal regression.xlsx' in Appendix 3).

Table 3.14. Stepwise linear regression for car ownership in Melbourne (2006)

Independent variables	Standardised coefficients	p-value	Variance inflation factor
Constant (-)	1.23	N/A	N/A
Population density (person/ha)	-0.28	0.04	1.84
Proportion of couples with children to other households (-)	0.33	0.01	1.57
Access to public transport (km)	0.23	0.03	1.23
Adjusted R^2 = 0.40			

Table 3.15. Stepwise linear regression for VKT in Melbourne (2006)

Independent variables	Standardised coefficients	p-value	Variance inflation factor
Constant (km)	3.44	N/A	N/A
Access to public transport (km)	0.44	0.00	1.04
Proportion of couples with children to other households (-)	0.43	0.00	1.04
Adjusted R^2=0.44			

Table 3.16. Stepwise linear regression for percentage of trips by car in Melbourne (2006)

Independent variables	Standardised coefficients	p-value	Variance inflation factor
Constant (%)	-11.70	N/A	N/A
Population density (person/ha)	-0.41	0.00	2.21
Household annual income ($)	0.43	0.00	1.61
Proportion of couples with children to other households (-)	0.21	0.01	1.56
Adjusted R^2=0.76			

Although in stepwise regression, all coefficients are significant, the overall explanatory power (adjusted R^2) is relatively low for car ownership and VKT (0.40, 0.44 respectively). It is not unusual in models based on large variation among SLAs, which cannot be quantified by specific variables. Consequently a linear regression model is not good enough for modelling travel behaviour at SLA level in Melbourne and therefore a log-linear model was investigated in the following section.

3.5.2. Log-linear regression model

Based on previous studies in land-use/transport interaction, it seems that some of land-use and socio-economic variables have non-linear effects on transport. For example, a common theme running through many of the car-ownership models is that car ownership increases with income level but the impact of income declines at a certain saturation level (Paravantis et al. 2007). Pongthanaisawan et al. (2010) developed a vehicle ownership model using a logistic function and found that vehicle ownership growth rate increases slowly by low income; as the level of income increases, vehicle ownership increases rapidly and finally the ownership growth rate slows down when car ownership reaches a saturation level. So the relationship between car ownership and income in not linear. On the other hand, Rickwood (2009) in considering the effect of population density on mode choice in Melbourne and Sydney found that there is a clear and non-linear relationship between higher density and greater public transport use, with the largest effects taking place up to 70 people/hectare. So based on these finding, a log-linear regression model for land-use/transport interaction was attempted. As a linear model provides poor correlations (low R^2) between travel behaviour indicators, socio-economic, and land-use factors, a log-linear model might enable better correlation in SLA levels in Melbourne. This hypothesis was tested by modelling car ownership, VKT and modal split using log-linear models.

- ***Car ownership***

  A log-linear model is a model that analyses the dependent and the independent variables in logarithm form. The estimated coefficients illustrate the dimension of relationship between dependent and independent variables. The general form of a log-linear regression equation can be written as (Limanond et al. 2011):

$$\ln(Y) = \alpha + \beta_1 \ln(X_1) + \beta_2 \ln(X_2) + ... + \beta_n \ln(X_n) \qquad 3.6$$

Y = Dependant variable

α = Constant

β = Coefficients

X = Independant variables

n = Number of independant variables

Independent variables in this model are socio-economic and land-use factors that correlate significantly with car ownership (Table 3.10) (see '2006\ non-linear model2006\car ownership.xlsx' in Appendix 3). The log-linear relationship between dependent and independent variables shows that some of the log-linear coefficients are conflicting with the results of correlations. For example, while the proportion of detached houses to other dwelling types is positively correlated with car ownership, the sign of the regression coefficient for the car-ownership model is negative (Table 3.17). This is because of the co-linearity among selected independent variables.

Table 3.17. Log-linear regression coefficients for car ownership in Melbourne (2006)

Independent variables	Standardised coefficients	p-value	Variance inflation factor
Constant (-)	-75.77	N/A	N/A
ln (household annual income) ($)	0.31	0.01	1.49
ln (proportion of couples with children to other household types) (-)	0.71	0.00	3.52
ln (population density) (person/ha)	-0.33	0.15	5.20
ln (access to public transport) (km)	-0.08	0.55	2.07
ln (proportion of detached houses to other dwelling types) (-)	-0.74	0.00	4.30
ln (walkability) (-)	-0.21	0.33	4.75
Adjusted R^2 = 0.38			

Following the same process as the linear-regression model, stepwise regression was used to eliminate the co-linearity problem (Table 3.18).

Table 3.18. Stepwise log-linear regression for car ownership in Melbourne (2006)

Independent variables	Standardised coefficients	p-value	Variance inflation factor
Constant (-)	0.34	N/A	N/A
ln (proportion of couples with children to other households) (-)	0.49	0.00	1.00
Adjusted R^2 = 0.23			

The results of the log-linear car-ownership model showed that log-linearity is not appropriate for showing the relationship between socio-economic, land-use factors and car ownership (R^2=0.23) (see '2006\ log-linear model-2006\car ownership loglinear.spv, car ownership log linear.xlsx' in Appendix 3).

- ***VKT***

The same approach was followed for estimating VKT using a log-linear regression model and stepwise model. Ln (VKT) is represented as a function of significant land-use and socio-economic factors (Table 3.19, 3.20) (see '2006\ log-linear model-2006\vkt log linear.xlsx, VKT loglinear.spv' in Appendix 3).

Table 3.19. Log-linear regression coefficient for ln (VKT) in Melbourne (2006)

Independent variables	Standardised coefficients	p-value	Variance inflation factor
Constant (km)	98.24	N/A	N/A
ln (household annual income) ($)	-0.17	0.15	1.74
ln (proportion of couples with children to other household types) (-)	0.23	0.12	2.52
ln (access to public transport) (km)	0.27	0.04	1.96
ln (distance from CBD) (km)	0.39	0.06	4.94
ln (walkability) (-)	-0.05	0.78	3.46
ln (car ownership) (-)	0.31	0.01	1.64
ln (area of SLA) (km^2)	-0.16	0.45	5.59
Adjusted R^2=0.46			

Table 3.20. Stepwise log-linear regression for ln (VKT) in Melbourne (2006)

Independent variables	Standardised coefficients	p-value	Variance inflation factor
Constant (km)	3.96	N/A	N/A
ln (proportion of couples with children to other household types) (-)	0.40	0.00	1.32
ln (access to public transport) (km)	0.27	0.01	1.09
ln (car ownership) (-)	0.26	0.02	1.39
Adjusted R^2=0.45			

Log-linear VKT model has nearly the same predictability compared to linear regression (R^2 is 0.45 in log-linear model compared to 0.44 in linear-regression model).

- ***Modal split***

  Modelling car trips with a log-linear model leads to the results shown in Table 3.21 and 3.22(see '2006\ log-linear model-2006\mode split log linear.xlsx, modal split log linear.spv' in Appendix 3). The model fits the data well compared to linear regression (i.e. higher R^2 in log-linear model compared to linear regression model).

Table 3.21. Log-linear regression coefficients for ln (percentage of trips by car) in Melbourne (2006)

Independent variables	Standardised coefficients	p-value	Variance inflation factor
Constant (%)	-88.99	N/A	N/A
ln (household annual income) ($)	0.45	0.00	1.62
ln (proportion of couples with children to other household types) (-)	0.43	0.00	1.88
ln (population density) (person/ha)	0.23	0.21	11.02
ln (access to public transport) (km)	-0.04	0.57	2.03
ln (walkability) (-)	-0.01	0.96	4.67
ln (car ownership) (-)	-0.06	0.38	1.63
ln (area of SLA) (km^2)	0.48	0.00	7.98
Adjusted R^2=0.81			

Table 3.22. Stepwise log-linear regression for ln (percentage of trips by car) in Melbourne (2006)

Independent variables	Standardised coefficients	p-value	Variance inflation factor
Constant (%)	-89.90	N/A	N/A
ln (household annual income) ($)	0.45	0.00	1.48
ln (proportion of couples with children to other households) (-)	0.44	0.00	1.41
ln (area of SLA) (km^2)	0.21	0.00	1.70
Adjusted R^2=0.81			

3.5.3. Neural network model

According to the non-linear modelling presented in the previous section, there is a strong non-linear relationship between the transport behaviour measurements and land-use and socio-economic factors. The artificial neural network (ANN) approach is superior to other modelling, as it can create complex functions that better fit the measured data. An ANN consists of several nodes working in parallel, and connecting to each other with a transfer function. The most popular type of ANN for transport modelling maybe a feed-forward network model. The general structure of feed-forward neural network consists of an input layer, an output layer and one or more hidden layers between inputs and outputs (Figure 3.2). The number of nodes in the input layer is usually equal to the number of inputs (or independent variables), while the number of nodes in the output layer is equal to the number of outputs (or dependent variables). Each node in the ANN is capable of receiving information from other nodes, processing the receiving data through a pre-defined processing function, and transmitting the output data to other nodes. ANNs have a variety of structures and different levels of complexity. The structure of the ANN, the number of layers/ nodes, and the processing function are the choices of the researcher (Limanond et al. 2011). After building of the neural network, the input data is fed into the network through the input nodes, along with the desired output data. This process is a training process of a neural network and the algorithms used for this process are training algorithms.

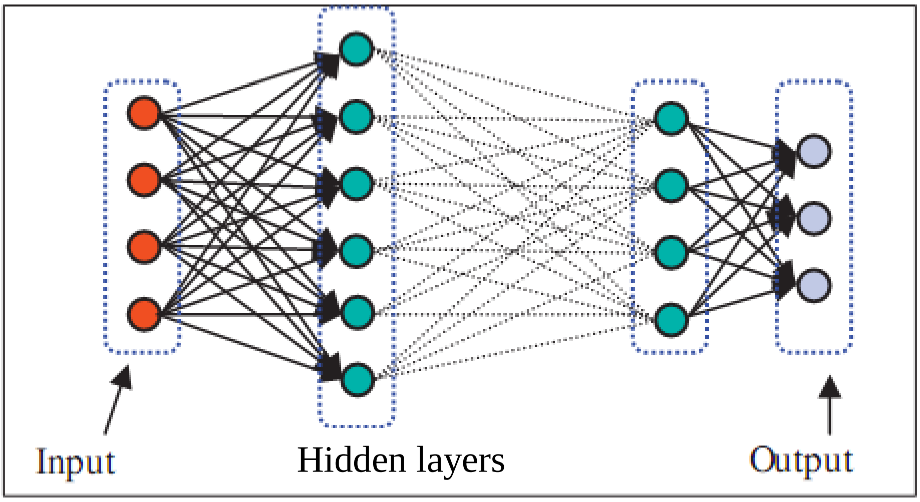


Figure 3.2. A structure of neural network (Limanond et al. 2011)

A back propagation algorithm is the most popular algorithm used for network training. When training data is fed as inputs to the model, the neural network assigns appropriate weights to each link in the network and calculates the outputs. The network sets up small random weights to calculate the outputs. Calculated outputs are different from the observed outputs, since the weights are random. Error (difference between observed and calculated outputs) is then calculated and used to change the weights in a way that the error reduces. The process is repeated until the error is minimal (Edara 2003).

The main deficiency of the ANN is that it does not show what the relationship between the inputs and the outputs is. In other words, the input variables are processed inside 'a black box' through non-linear computations (Limanond et al. 2011). Some researchers criticise neural network modelling as it does not provide an equation that can be used for prediction. But, it should be noted that the trained network can be directly used on new data for predicting the output (Edara 2003).

In term of an ANN application for transport modelling, there are some examples of ANN application in transport energy-demand modelling. In recent years, neural networks are being used instead of regression techniques for travel-demand forecasting purposes. For example, Murat et al. (2006) used supervised neural networks to forecast transport-energy demand based on GNP, population, and VKT for 2020. Comparing model predictions with energy data in testing periods confirmed that ANN can reflect historical data trends for both dependent and independent variables and so it is a suitable method for transport-energy forecasting. Limanond et al. (2011) used log-linear and feed forward neural network models to predict transport energy consumption for the next 20 years, using GDP, population, and the numbers of registered vehicles as independent variables. The results of their study showed that log-linear regression model provides projections that are slightly higher than projections from ANN. Edara (2003) compared ANN model and linear regression model to predict mode choice. Based on the mean square error, average relative variance, and residuals estimates, it was concluded that the ANN model provides better results than linear regression models.

Based on the literature, there was no attempt to model land-use/transport interaction using ANN model. This study tried to use ANN to estimate car ownership, VKT and modal split as functions of selected land-use and socio-economic factors, and compared the results with results of the two previous modelling techniques presented. The ANN model, which was used in this study, is a feed forward network. The neural network analysis was implemented for Melbourne data in Matlab. Car ownership, VKT and modal split were introduced to the Matlab Neural Network Fitting Tool as outputs and selected socio-economic and land-use factors were introduced as inputs (see '2006\NN-2006\carownership.m,vktmodel.m,modalsplitmodel.m' in Appendix 3). 70% of data were used for training, 15% for validation and 15% for testing, which is the default setting in Matlab. When training data is fed as inputs to the model, the neural network assigns appropriate weights to each link in the network and calculates the outputs. Validation data is not directly used for training purpose but it is used for validation purposes during the training process. Testing data has no effect on training and so provides an independent measure of network performance during and after training (Edara 2003). A number of hidden neurons were set at 10, which is the default setting in Matlab.

Corresponding mean square error (MSE) and R^2 value for car ownership, VKT, and modal split models are provided in Table 3.23 MSE is the average squared difference between observed and estimated variables (Equation 3.7), and R^2 measures the correlation between observed and estimated variables. Low MSE and high R^2 shows that ANN is capable of modelling transport behaviour as a function of socio-economic and land-use factors. (see '2006\NN-2006\carownership.m, carownershipInput.xlsx, car ownershipTarget.xlsx, car ownership NRMSE.xlsx,vktmodel.m, VKT input.xlsx, VKT target.xlsx, VKT RMSE.xlsx, modalsplitmodel.m, modal split input.xlsx, modal split target.xlsx, RMSE modal.xlsx' in Appendix 3).

$$MSE = \frac{\sum^{n}\left(Y_{obs} - Y_{model}\right)^2}{n} \qquad 3.7$$

$n =$ Total number of data

$Y_{obs} =$ Observed data

$Y_{model} =$ Estimated data by the model

Table 3.23. MSE and R^2 values from neural network models

	MSE	$\mathbf{R^2}$
Car ownership (-)	0.03	0.66
VKT (km)	0.06	0.75
Modal split (%)	0.002	0.93

3.6. Modelling techniques comparison

To test the models ability to estimate car ownership, VKT and percentage of trips by car as functions of selected land-use, socio-economic factors, developed models were verified using Melbourne (2006) SLAs data. R^2 and root mean square error (RMSE) (Equation 3.8) were used to compare observed versus estimated car ownership, VKT and percentage of trips by car in Melbourne. The smaller the RMSE, the closer are the estimations to the observed data. However, the RMSE values can only be used to indicate model performance, as they have units. So, RMSE value for one model cannot directly compare to RMSE values for other models. In this case, normalised RMSE (NRMSE) (Equation 3.9) was used to compare the models' errors.

$$RMSE = \sqrt{MSE} \tag{3.8}$$

$$NRMSE = \frac{RMSE}{\overline{Y_{obs}}} \tag{3.9}$$

Where $\overline{Y_{obs}} = \text{Mean of observed data}$

Models NRMSE and R^2 are shown in Table 3.24.

Table 3.24. R^2 and NRMSE for land-use/transport interaction models for the whole sample

	Car ownership		**VKT**		**Modal split**	
	NRMSE	R^2	NRMSE	R^2	NRMSE	R^2
Linear regression model	26.83%	0.40	22.56%	0.44	1.54%	0.76
Log-linear regression model	95.26%	0.23	9.77%	0.45	2.12%	0.81
Neural network model	14.87%	0.66	6.11%	0.75	0.97%	0.93

3.7. Primary fuel consumption and GHG emissions

Estimated car ownership, VKT and percentage of trips by car, which were the outputs of the ANN model were used to estimate the primary fuel (crude oil) consumption and its related GHG emissions. Estimated transport crude oil consumption and its related GHG emissions for each SLA in Melbourne are shown in Figure 3.3, 3.4 (see '2006\environmental indicators\energy and emission1.xlsx' in Appendix 3).

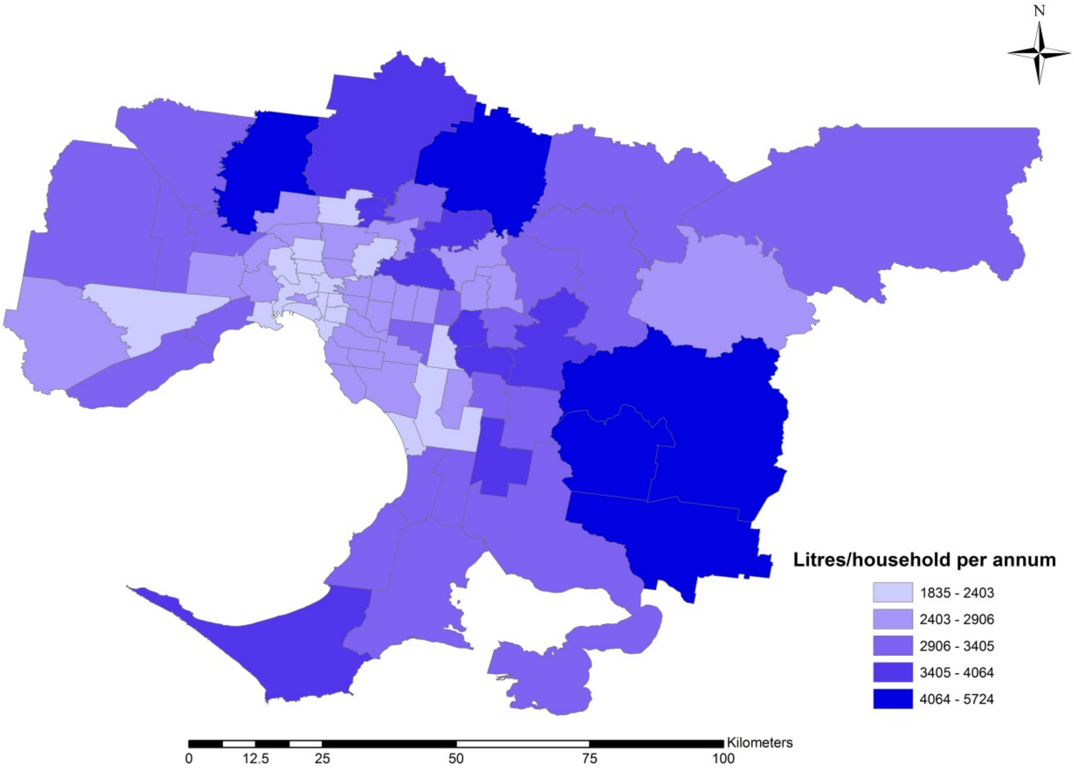


Figure 3.3. Primary fuel consumption (Litres/household) in Melbourne (2006)

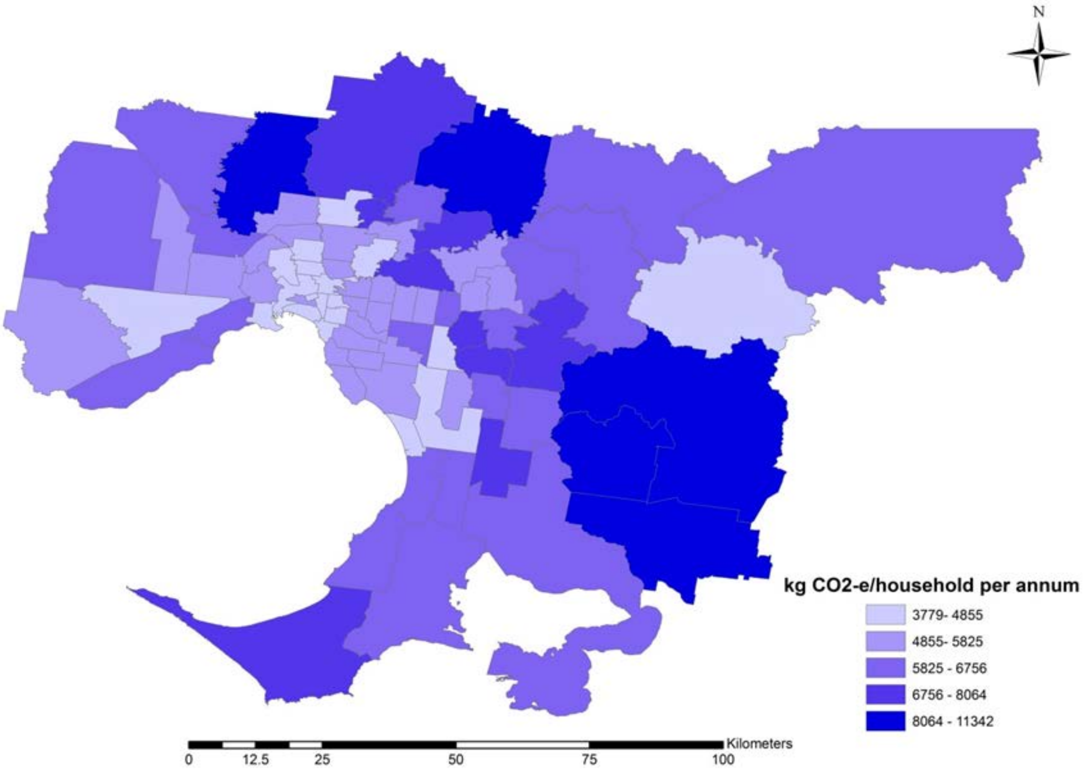


Figure 3.4. GHG emissions (kg CO_2-e/household) in Melbourne (2006)

3.8. Land-use effects on transport behaviour compared to socio-economic factors

Modelling studies on the effects of land-use and socio-economic factors on travel behaviour concluded that land-use factors affect car ownership, VKT and percentage of trips by car as travel behaviour measurements. A critical argument raised from this conclusion is that certain types of land-use patterns attract residents with specific socio-economic profile. For example, households without children usually live in high population density areas (Kitamura et al. 1997). So socio-economic attributes of residents are the true determinants of travel behaviour and that land-use factors by itself may not affect travel behaviour.

To consider this argument, this section seeks to answer the following questions: "Are travel behavior directly linked with land-use factors, or is it the result of the link between land-use and household socio-economic characteristics?" To answer this question, ANN models were first developed for car ownership, VKT and percentage of trips by car, using selected socio-economic factors, which are called 'base' models. Then, land-use factors were introduced into the 'base' models one at a time to examine the association between travel behaviour measures and selected land-use factors. The effect of each land-use factor on models' estimation ability was examined using NRMSE and then, in the final stage the models were developed considering all land-use factors, as well as socio-economic factors (Table 3.25) (see '2006\NN-2006\ .m files). The introduction of land-use factors into the base models reduces NRMSE. So, it could be concluded that land-use factors do contribute to the models' estimation ability, independent from socio-economic factors.

Table 3.25. Contribution of individual land-use factors to the estimation ability of land-use/transport interaction models (The number in each cell is NRMSE (%))

	Car ownership	**VKT**	**Modal split**
Base model (considering only socio-economic factors)	15.4	8.6	1.4
Base model plus population density	15.2	N/A	1.01
Base model plus distance to the CBD	N/A	7.5	N/A
Base model plus dwelling type	12.9	N/A	N/A
Base model plus access to public transport	14.4	6.7	1.2
Base model plus SLA area size	N/A	5.8	1.1
Base model plus walkability	14	7.5	1.1
Base model plus all land-use factors	12	5.9	0.9

3.9. Chapter summary

This chapter describes environmental indicators selected for transport sustainability. Depletion of non-renewable resources, GHG emissions, other air pollutants emissions, and land devoted to transport were selected as environmental indicators based on the literature review, using the selection criteria defined. Then different modelling techniques were used to model car ownership, VKT and percentage of trips by car as functions of socio-economic and land-use factors. The results obtained from different techniques (linear regression model, log-linear regression model, and ANN model) showed that the ANN model is the most appropriate (i.e. provides higher R^2 and lower NRMSE) for modelling land-use/transport interaction. Moreover, effects of socio-economic and land-use factors on the estimation of travel behaviour measurements were evaluated. The results showed that land-use factors affect travel behavior, independent from socio-economic factors. After quantifying transport energy consumption and emissions, their social and economic impacts on transport sustainability will be quantified in the next chapter.

Chapter 4

Social and Economic Indicators

4.1. Introduction

Sustainable transport, as one of the important dimensions of urban sustainability, has been developed to achieve a balance between transport socio-economic benefits and its social and environmental adverse effects. This means that evaluating sustainable transportation should consider possible impacts on the environment (e.g. pollution, resource depletion, and global warming), economy (e.g. direct and indirect transportation costs), and society (e.g. human health impacts, accessibility, equity, and safety problems). In the previous chapter, selected environmental indicators were quantified using an integrated land-use/transport interaction model. The results of the model (transport energy consumption and emissions) are used to quantify selected social and economic indicators in this chapter. Selected social and economic indicators are the ones that meet the indicators selection criteria, discussed in Chapter 3.

4.2. Transport social indicators

Road transportation, which is an important dimension of urban sustainability, has significant environmental, social and economic impacts (Haghshenas et al. 2012). As mentioned before, indicators play a major role in measuring sustainable transport (Dobranskyte-Niskota et al. 2007). Social indicators are an important part in transport sustainability assessment. A sustainable transport system should provide accessibility for all people and also minimise hazards to health and the risks of traffic accidents (Castillo et al. 2010). For selecting social indicators in this study, firstly a literature review was done. The most frequently used transport-related social indicators are provided in Table 4.1. These indicators are sorted out based on the number of times they are mentioned as social indicators in transport sustainability research. According to the most cited indicators (Table 4.1) and the criteria for indicator selection (Table 3.2), selected social indicators for the study area are presented in Table 4.2. According to the selection criteria, these indicators are quantifiable based on available data for the study area, are independent and can be understood by users easily. As there is no data available for injuries related to air pollutants, only mortality effects of air pollutants were quantified in this study. Moreover, the quality of transport options and satisfaction of citizens are hard to quantify; therefore, they were not included in the selected social indicators list.

Table 4.1. Transport-related social indicators

Transport-related social indicator	Frequency of use	References
Fatalities and injuries related to traffic accidents	10	Castillo and Pitfield (2010), D'Amico et al. (2012), Dobranskyte-Niskota et al. (2007), Gilbert et al. (2002), Haghshenas and Vaziri (2012), Jeon and Amekudzi (2005), Kolak et al. (2011), Litman (2009), Spiekermann and Wegener (2004), Tanguay et al. (2010)
Accessibility to facilities and public transport	8	Castillo and Pitfield (2010), Dur et al. (2010), Haghshenas and Vaziri (2012), Jeon and Amekudzi (2005), Spiekermann and Wegener (2004), Zegras (2006), Dobranskyte-Niskota et al.(2007), Kolak et al. (2011)
Quality of transport for disadvantaged, disabled, children, non-drivers	5	Haghshenas and Vaziri (2012), Dobranskyte-Niskota et al. (2007), Jeon and Amekudzi (2005), Kane (2010), Litman (2009)
Satisfaction of citizens and variety and quality of transport options	3	Awashti and Chauhanet (2011), Haghshenas and Vaziri (2012), Litman (2009)
Fatalities and injuries resulted from air pollutants	3	Dobranskyte-Niskota et al. (2007), Jeon and Amekudzi (2005), Zegras (2006)
Proportion of residents with public transit services within 500 m	3	D'Amico et al. (2012), Jeon and Amekudzi (2005), Kane (2010)

Table 4.2. Selected social indicators for Melbourne

Selected indicators for the study	Unit
Accessibility	score between 0 and 1
Fatalities and injuries related to traffic accidents	persons per household annually
Mortality effects of air pollutants	persons per household annually

4.3. Quantifying social indicators

For measuring transport sustainability, selected social indicators (Table 4.2) must be quantified. So indicator quantification is the second step, after indicator selection, in transport sustainability measurement. As mentioned before, the results of the land-use/transport interaction model, along with ABS database and VISTA07 were used to quantify the selected social indicators.

4.3.1. Accessibility

Accessibility, as the main goal of transport, is a frequently-used concept; however, there is no agreement about its definition and measurement (Vandenbulcke et al. 2009). It is commonly defined as the ability to reach desired goods, services, activities, and destinations (Litman 2009). Accessibility can be used as a social indicator if it shows the availability of social and economic opportunities for people (Geurs et al. 2004). Assessing accessibility can also show equity issues and transport disadvantages. This is desirable because socially equitable transport systems must provide a fair distribution of transport services and equal access to facilities (Pitot et al. 2006). Several types of accessibility measures have been used in transport-planning studies. The most commonly used measures are:

- Gravity measures: These measures are derived from the gravity model of spatial interaction, which suggests that accessibility is positively related to the attractiveness of destinations and negatively related to the travel impedance between origins and destinations (Apparicio et al. 2006; Lotfi et al. 2009; Makri et al. 1999; Zhang et al. 2011).

- Distance measures: These measures are the simplest accessibility measures, measuring the distance from one location to different facilities. It can be measured as average distance, weighted area distance or distance to the closest opportunity (Apparicio et al. 2006; Lotfi et al. 2009; Makri et al. 1999).

- Cumulative-opportunity measures: Accessibility is evaluated with regard to the number or proportion of facilities accessible within a certain travel distance or time from an origin (Apparicio et al. 2006; Lotfi et al. 2009; Makri et al. 1999).

- Utility-based measures: Utility theory is based on the assumption that individuals will maximise their utility. This means that the individual gives each destination a utility value, and that the likelihood of choosing a particular destination depends on the utility of that choice compared to the utility of all choices (Makri et al. 1999).

There is no best approach for accessibility measurement because different situations and purposes need different approaches (Geurs et al. 2004). As the objective of the accessibility index in this study is to describe the proximity of SLAs to a series of facilities, distance measures and cumulative opportunity measures were selected to quantify accessibility by walking and public transport. Four types of distances can be used to calculate measures of accessibility: Euclidian distance (straight-line), Manhattan distance (distance along two sides of a right-angled triangle), shortest network distance, and shortest network time. Network distance is a more accurate approximation of the travel distance from an origin to a destination (Apparicio et al. 2006) and so it was selected for this study.

In this study, a GIS-based methodology was used to measure accessibility to common destinations by walking and public transport. The basic data needed were road and public transport networks, geographic coordinates of public transport stations, and location of origins and destinations. Data representing the road and public transport networks were obtained from the Department of Transport. Land-use maps showing different facilities (destinations) were obtained from the Department of Sustainability and Environment. It is worth mentioning that considering SLAs as points of origins may give misleading results, as SLAs are normally large and accessibility is not the same for different parts of one SLA. To overcome the problem, accessibility was quantified at the CCD level, and then the results were aggregated to SLA level. CCDs are small enough to provide precise accessibility measures. First, accessibility by walking is quantified as follows:

1. select the centre of a CCD as the point of origin which corresponds to the geometric centre of the CCD;

2. select parks, education facilities, health services, public transport stations, and business zones as points of destination;

3. select road network;

4. find shortest network distance between origin and destination, using ArcGIS 9.2 Network Analyst Extension;

5. use fuzzy linear function to weight the CCD for the level of accessibility to each destination according to the calculated distance in Step 4. Compared to traditional binary sets (where CCDs may be considered as accessible or non-accessible), fuzzy logic provides accessibility index that ranges between 0 and 1. Fuzzy logic handles the concept of partial accessibility, which ranges between completely accessible and completely non-accessible (Hellman 1968).

The fuzzy linear function applies a linear function between the user-specified minimum and the maximum appropriate distances to each destination (Table 4.3). Anything less than the minimum distance will be assigned a '1' value and anything above the maximum distance will be assigned a '0' value (ESRI 1999); where 0 shows no accessibility to the destination and 1 shows full accessibility to the destination. For example, it was assumed that CCDs with less than 500 m distance from parks have full accessibility (full fuzzy) and CCDs with more than 1500 m distance from parks have no accessibility (fuzzy-less), and the fuzzy linear function is assigned fuzziness between 500 and 1500 m (Equation 4.1).

$$F(x)=\left\{\begin{array}{ll} 1 & x<500\,m \\ \dfrac{x_{\max}-x}{x_{\max}-x_{\min}} & 500\,m<x<1500\,m \\ 0 & x>1500\,m \end{array}\right\} \qquad 4.1$$

$x=$ Shortest network distance between origin and destination (m)
$x_{\max}=$ Maximum appropriate distance to each destination (m)
$x_{\min}=$ Minimum appropriate distance to each destination (m)

Appropriate travel distances to facilities are shown in Table 4.3. As there are no appropriate distances to tram stations available in the literature, it was assumed that the appropriate distance to tram stations is between the appropriate distances to bus and train stations. This assumption is because of the higher frequency of trams compared to buses, as well as its lower coverage compared to trains.

Table 4.3. Appropriate travel distance to facilities (minimum and maximum values) (Green et al. 2011; Kellett et al. 2009; Pitot et al. 2006)

Facilities	Appropriate distances for accessibility by walking
Business centres	800–1600 m
Health centres	600–1200 m
Education centres	600–1200 m
Parks	500–1500 m
Public transport stations	300–1000 m for bus stations 450–1100 m for tram stations 600–1200 m for train stations

6. Average all walkability measures to different destinations (access to parks, education facilities, health services, public transport stations, and business) into a final walkability index for the CCD. Finally, the walkability indices of the CCDs that belong to one SLA were averaged to estimate the walkability for each SLA.

In the next phase, accessibility to different facilities using public transport was quantified as follows:

1. Select public transit stops (called PTS X for clarification) on the road network that are within a specific walking distance (Table 4.4) from each destination.

2. Select public transit stops (called PTS Y for clarification) on public transit routes that are within a given travel time (Table 4.4) from PTS X. As there is no information available about travel time, the travel distances were converted to travel time assuming 38 km/h for train speed, 14 km/h for tram speed, and 20 km/h for bus speed. Moreover, as there is no information available for parks, it was assumed that the appropriate walking distance and appropriate travel time to parks using public transport are the same as that for health and education services.

3. Find the shortest network distance in the road network between PTS Y and the CCD centres, using ArcGIS 9.2 Network Analyst Extension.

4. Use fuzzy linear function to weight each CCD for the level of accessibility to the nearest PTS Y according to the calculated distance in Step 3. This step would be the same as Step 5, which was done for quantifying the walkability index.

5. Average all accessibility measures to different destinations (access to parks, education facilities, health services, and business) by different modes of public transport (bus, tram and train) into a final accessibility index by public transport for the CCD. Finally, the CCDs accessibility indices by public transport that belong to one SLA were averaged to estimate the accessibility for each SLA.

In the final phase, the walkability index and accessibility index by public transport were aggregated into a single index (using the average of walkability and accessibility by public transport), which shows overall accessibility for each SLA.

Table 4.4. Accessibility by public transport (Pitot et al. 2006)

Facilities		**Walk to public transport**	**Travel time via public transport**
Business centres	Bus	300–1000 m walk	20–50 min travel time
	Tram	450–1100 m walk	20–50 min travel time
	Train	600–1200 m walk	20–50 min travel time
Health centres	Bus	400–1000 m walk	20–40 min travel time
	Tram	600–1100 m walk	20–40 min travel time
	Train	800–1200 m walk	20–40 min travel time
Education centres	Bus	400–1000 m walk	20–40 min travel time
	Tram	600–1100 m walk	20–40 min travel time
	Train	800–1200 m walk	20–40 min travel time
Parks	Bus	400–1000 m walk	20–40 min travel time
	Tram	600–1100 m walk	20–40 min travel time
	Train	800–1200 m walk	20–40 min travel time

Figure 4.1 presents a visual representation of the quantified accessibility index in Melbourne for 2006. Approximately 75% of the SLAs within Melbourne have low to medium levels of accessibility; another 19% of them have poor levels of accessibility; and SLAs which benefit from high levels of accessibility account for 6% of the SLAs. While most of the SLAs have high accessibility by public transport, the majority of Melbourne SLAs have poor access by walking (Table 4.5).

Table 4.5. Range of accessibility in Melbourne SLAs (%)

	Poor (0–0.2)	**Low (0.2–0.4)**	**Medium (0.4–0.6)**	**High (0.6–0.8)**	**Excellent (0.8–1)**
Accessibility by walking	16	35	40	9	0
Accessibility by public transport	27	48	21	4	0
Overall accessibility	19	50	25	6	0

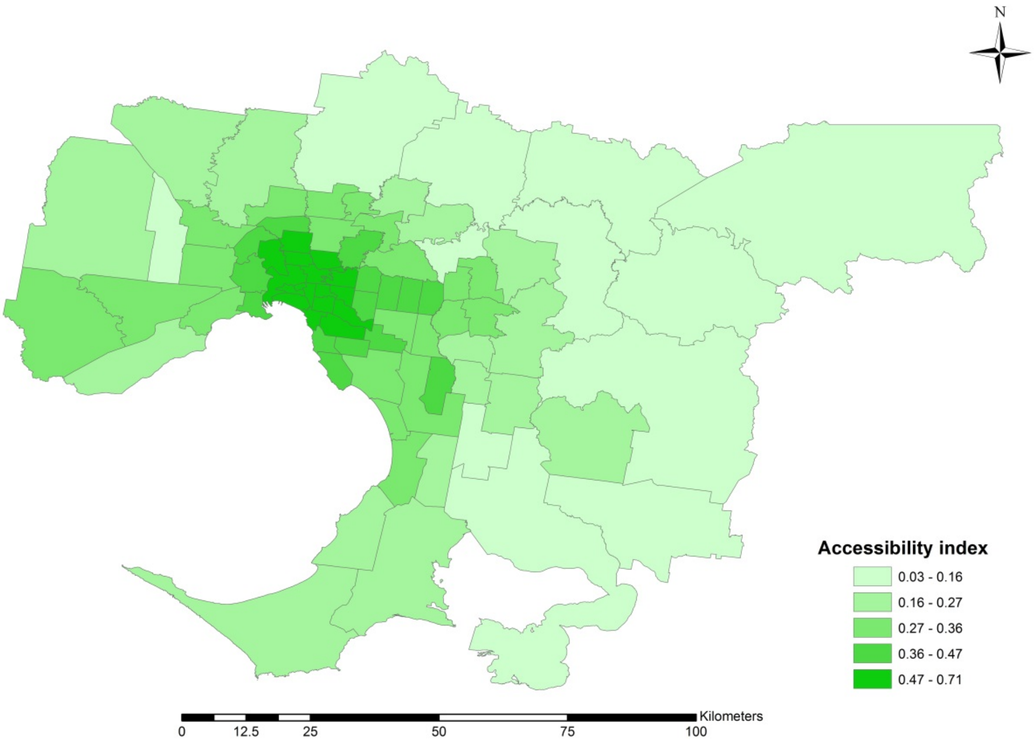


Figure 4.1. Accessibility index (Melbourne, 2006)

Methods discussed in this section were used to quantify accessibility by walking and public transport as one of the selected social indicators for transport sustainability. Methods for quantifying other selected social indicators were provided in the following sections.

4.3.2. Fatalities and injuries related to traffic accidents

Transportation systems are crucial components of modern societies. Although they have good economic and social benefits, they are not without costs. Transportation is increasingly associated with an increase in road accidents and premature deaths, as well as physical and psychological handicaps (Peden et al. 2004). Road traffic injuries are the ninth leading cause of death worldwide, and by 2030 it is expected to become the fifth leading cause of death (Naumann et al. 2010). A sustainable transport system should be designed and operated in a way that minimises the number, severity and risk of traffic accidents (Castillo et al. 2010). So, safety is one of the requirements of a sustainable transport system (Gilbert et al. 2002). Based on road crash casualties and rates in Australia, which was produced and published by the Australian Transport Safety Bureau (ATSB) in 2007, there were 0.8 deaths and 14.8 serious injuries per 100 million vehicle kilometres travelled (VKT) (ATSB 2007). To our knowledge, there is no available published data for crash fatalities and injuries disaggregated for Melbourne. Therefore, the Australian average data was used in this study. Moreover, there is no census information available for fatalities and serious injuries related to accidents at the SLA level in Melbourne. So, it was assumed that the number of crash fatalities and serious injuries are directly related to VKT. Moreover, deaths and injuries rates related to public transport assumed one-tenth of the rates related to private transport (Litman 2013). Therefore, based on the above figures and VKT, which was calculated in Chapter 3, it was estimated that 162 people have died and 2998 people have been seriously injured due to traffic accidents in Melbourne in 2006. Figures 4.2 and 4.3 show household annual crash-related deaths and injuries in Melbourne SLAs in 2006. (see ‘2006\social indicators – 2006\ death due to accident 2006.xls’ in Appendix 3).

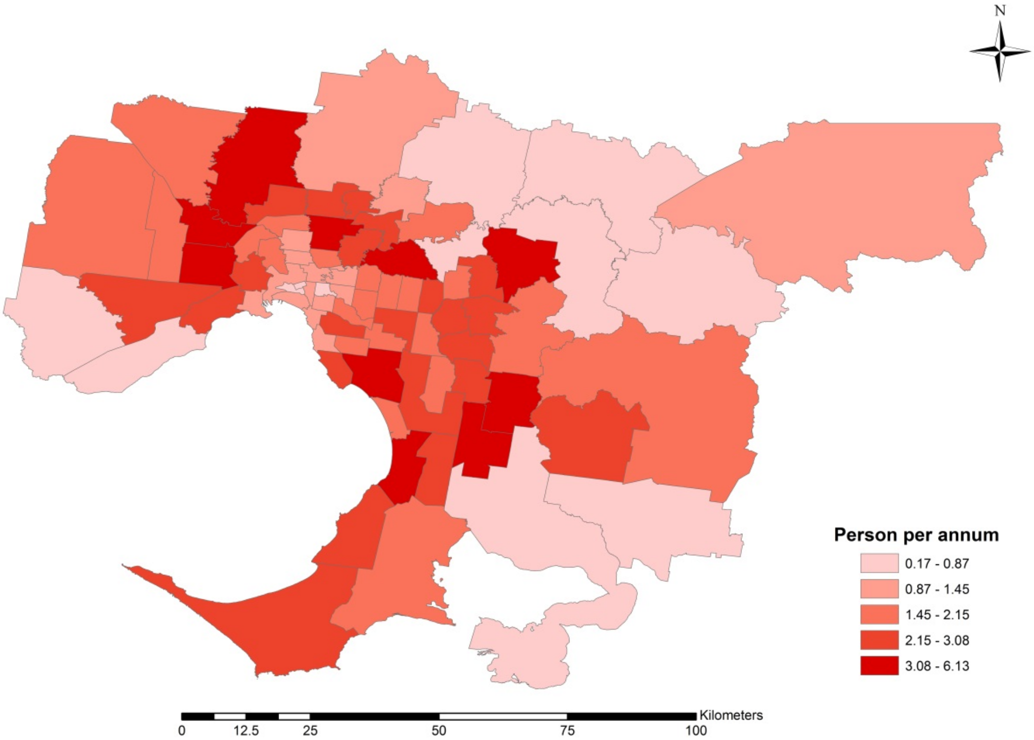


Figure 4.2. Annual crash-related deaths (Melbourne, 2006)

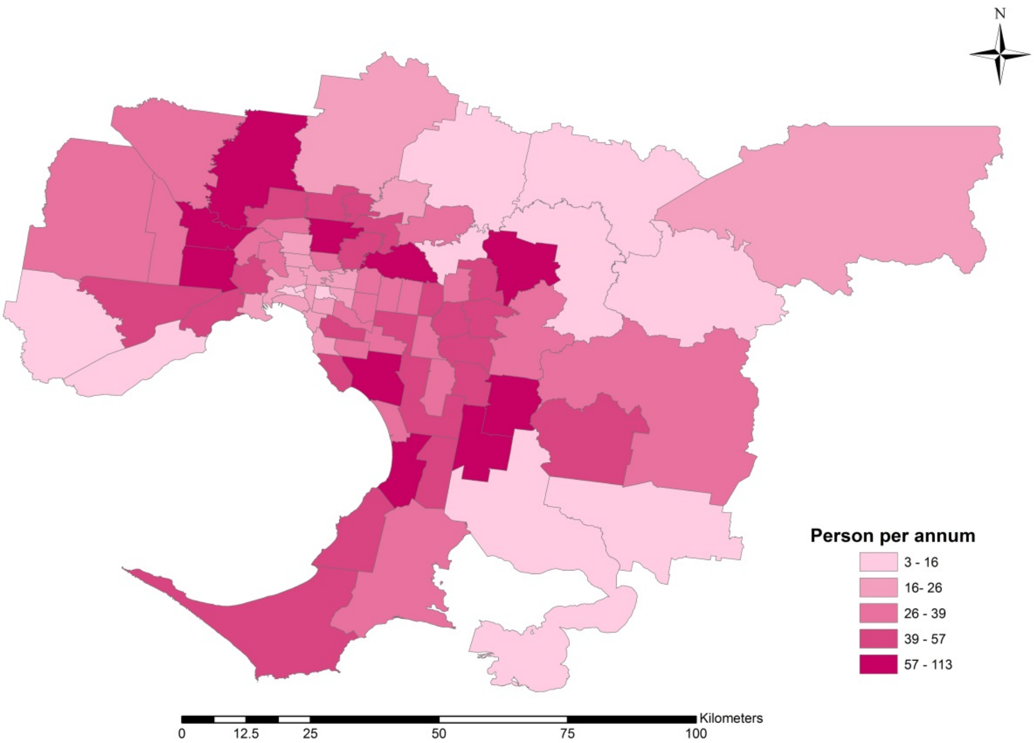


Figure 4.3. Annual crash-related injuries (Melbourne, 2006)

4.3.3. Mortality effects of air pollutants

Road transport is the main cause of poor air quality. In Australia, motor vehicles account for over half of the emissions of nitrogen oxides and carbon monoxide, and almost half of the emissions of hydrocarbons. More specifically, motor vehicles are a significant source of air pollutants in the Melbourne metropolitan area. The health effects of air pollutants include short-term (acute) and long-term (chronic) effects. These effects include immediate irritation to eyes and throat, and hospitalisation and even death from respiratory failure (Brindle et al. 1999).

Considering the health impacts of air pollution began with smog episodes in European and USA cities, such as the London fog episodes during 1952 and 1958. Analysis of data for London showed that mortality was associated with air pollution over the entire range of ambient concentrations, not just with high pollution concentrations (Ostro 2004). Additional evidence about the health effects of air pollution is provided by a study using data in 100 metropolitan areas in the USA. It was reported that existing sulphate concentrations correspond to a 4% to 9% increases in mortality, while 10 $\mu g/m^3$ PM_{10} corresponds to a 0.92% to 2.06% changes in all-cause mortality (Özkaynak et al. 1987). Epidemiological studies have shown that ozone (O_3) levels are associated with hospital admissions and emergency visits for respiratory disease (including asthma) and with increases in respiratory symptoms, as well as decreases in lung function. There is also evidence that O_3 may be associated with an increase in daily mortality, mainly in the elderly and in people with existing cardiovascular or respiratory diseases (EPA 2000).

Epidemiological studies during the 1990s revealed that people’s health may be affected by exposure to much lower levels of some common air pollutants than believed. This suggests that despite a significant reduction in the concentrations of many pollutants, the adverse health effects still occur in most countries. Hence, even though Australia may be regarded as a low pollution country, a potential health risk remains (Kunzli et al. 1999). Assessing the effects of air pollution on health relies on estimating the number of diseases due to air pollution. The components required to estimate the number of health cases attributed to a specific air pollutant in a given population are as follows (Coffey 2003):

- exposure-response function (relative risk from an epidemiological study);
- frequency of the health outcome (the incidence of the health outcome);
- level of exposure to the air pollutant.

Relative risk (RR) is one of the most common measures of health effects used to report results in epidemiologic studies. The RR is the ratio of risk, which is shown by a value between 0 and 1; whereby RR 1 is the risk of experiencing some health outcomes among an exposed population, and RR 0 is the risk of health outcomes among an unexposed population (Künzli 1999). There are some methods for estimating the number of mortalities due to transport-related air pollution. One of these methods was proposed by Kunzli et al. (1999). In the first step, the baseline mortality (which is defined as the proportion of population that would die because of air pollutants) is calculated from the observed mortality in the population calculated by Equation 4.2:

$$P_0 = \frac{P_e}{1 + \left[(RR - 1)(E_0 - B)/10\right]} \qquad 4.2$$

where

P_0 = Base mortality (number of deaths)

P_e = Observed mortality in the population (number of deaths)

E_0 = Observed mean pollutant exposure level (μg/m^3)

B = Pollutant exposure level for mortality effect (μg/m^3)

RR = Relative risk for 10 units increase in the pollutant (-)

Then, the number of additional mortalities per one million people, attributable to a 10 unit increase in the pollutant is calculated by Equation 4.3, given below:

$$D_{10} = 1000000\, P_0\, (RR - 1) \qquad 4.3$$

D_{10} = Number of additional deaths per one million people for a 10 units increase in the pollutant (number of deaths)

RR = Relative risk for 10 units increase in the pollutant (-)

Finally, in the last step, the number of deaths due to the pollutant for the whole population is calculated by Equation 4.4:

$$N_c = D_{10}\ P_c / 1000000 \left[\left(\frac{E_0 - B}{10}\right)\right] \qquad 4.4$$

N_c = Number of deaths due to the pollutant for a given population (number of deaths)

D_{10} = Number of additional deaths per one million people for 10 units increase in the pollutant (number of deaths)

P_c = Population (number of people)

E_0 = Observed mean pollutant exposure level (µg/m^3)

B = Pollutant exposure level for mortality effect (µg/m^3)

Another method was proposed by Ostro (2004). The expected number of deaths due to air pollution can be calculated by Equation 4.5(Ostro 2004):

$$E = AF\ B\ P \qquad 4.5$$

E = The expected number of deaths due to air pollution (number of deaths)

B = The population incident of mortality (number of deaths per people)

P = The relevant exposed population for the health effect (number of people)

$$AF = \frac{RR - 1}{RR} \qquad 4.6$$

AF = The impact fraction of the health effect for the exposed population (-)

RR = Relative risk of air pollutant (-)

An important question related to the expected number of deaths due to air pollution is which of the air pollutants must be considered. Air pollution is a mixture of different substances. The total impact of air pollution on health may be considered as the sum of all independent effects of specific pollutants, the effects of mixtures, and the additional effects due to interactions between pollutants. Many air pollutants are highly correlated due to their common sources. So, one or a few indicators of air pollutants must be selected in impact assessment. The impact assessment ought to rely on indicators of air pollutants for which epidemiological evidence is strong and for which effects estimates are available (Künzli 1999).

For solving such a problem, most available studies use PM_{10} as a useful indicator of the health risk of transport sources. Although PM_{10} may be a good indicator of air pollution, there is clear evidence that other pollutants, which are poorly correlated with PM_{10}, may have independent health effects. One such example is ozone as an indicator of oxidant pollution (Künzli 1999). Moreover, according to the State of the Environment report (2001), there was little evidence in the capital cities of Australia of air pollution problems due to carbon monoxide, sulphur dioxide, nitrogen dioxide or lead; however, particulate and ozone concentrations remain a concern in Melbourne with no clear downward trend (Coffey 2003). As Kunzli's method needs an annual mean level of pollutants and this information is not available for the study area in the SLA level (because the parameter that was estimated in this study was annual cumulative concentration of air pollutants), this method is not suitable for this study. So using relative risk of death for PM_{10}, 1.0009 and ozone, 1.0023 (EPA 2000), the expected number of deaths due to air pollution (Figure 4.4) was estimated using Ostro's method (Equations 4.5 and 4.6). SLAs with more population have higher death rate related to air pollution. It was estimated that 20 people died from PM_{10} and 51 people died from ozone in Melbourne in 2006 (see '2006\ social indicators-2006\ death due PM_{10}.xls' in Appendix 3).

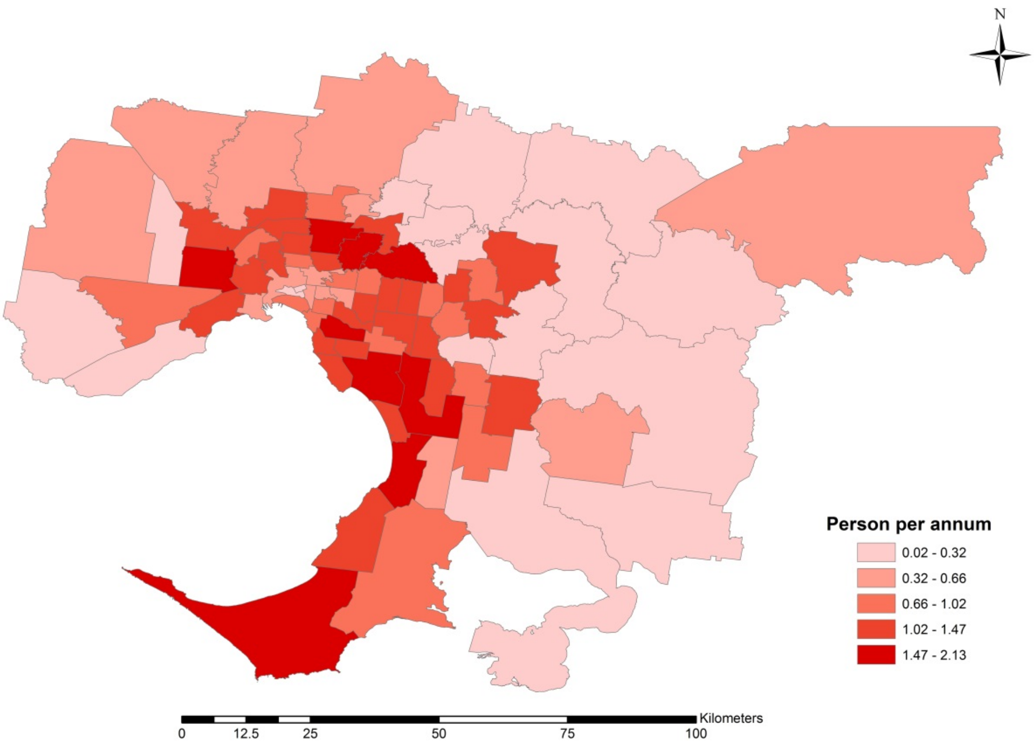


Figure 4.4. Annual pollution-related deaths (Melbourne, 2006)

4.4. Transport economic indicators

Negative environmental and social impacts of transport impose large costs to society. These costs are estimated to be at least 5% of GDP for industrialised countries (Nijkamp et al.

2011). A sustainable transport system must contribute to economic growth and must also reflect all costs related to transport activities (Castillo et al. 2010). Communities need accurate and comprehensive information on transport-related costs when making transport policy and planning decisions (Litman 2003). The most frequent transport-related economic indicators are provided in Table 4.6. These indicators were sorted out based on the number of time they were mentioned as economic indicators in transport sustainability research. Based on the defined selection criteria, selected economic indicators for this study are shown in Table 4.7. Although air pollution is a commonly recognised cost of motor vehicle use, it was not selected in this study. The reason is that fatalities related to air pollutants are considered as one of the social indicators in this study. So considering emission costs may double-count the effects. Moreover, based on the vast literature review on transport sustainability studies, there is no study that tries to evaluate the benefit of active and public transport. However, comprehensive economic evaluation needs both benefits and costs to be considered. So this study tried to consider economic benefits of active and public transport as economic indicators. On the other hand, total time spent in traffic and congestion costs as important economic indicators are not considered in this study due to lack of data for the study area.

Table 4.6. Transport economic indicators

Transport economic indicator	Frequency of use	References
Household expenditure allocated to transport	8	Dobranskyte-Niskota et al. (2007), Dur et al. (2010), Gilbert et al. (2002), Haghshenas and Vaziri (2012), Jeon and Amekudzi (2005), Kane (2010), Litman (2009), Nicolas et al. (2003)
Total time spent in traffic and congestion costs	6	Haghshenas and Vaziri (2012), Kane (2010), CST (2003), Marsden et al. (2005), Brownstone and Small (2005), Hamilton (2003)
Transport emissions costs	5	Litman (2009), Delucchi et al. (1996), Wang et al. (1995), Bein (1997), Spiekermann and Wegener(2004)
Accident costs	4	Litman (2009), Jeon and Amekudzi (2005), Kane (2010), Spiekermann and Wegener (2004)
Vehicle costs	4	Litman (2009), CAA (2007), Polzin et al. (2008), Barnes and Langworthy (2004)
Noise costs	4	Litman (2009), USDOT (1997), Delucchi and Hsu (1998), Haling and Cohen (1997)
Costs of parking	3	Nicolas et al. (2003), Litman (2009), Shoup (2005)
Transport taxes and subsidies	2	PI (2001), EEA (2002)
Fuel price	1	EEA (2002)

Table 4.7. Selected economic indicators for Melbourne

Selected indicators for the study	Unit
Car ownership costs and operation costs of public transport	$ per household annually
Vehicle and general costs of accidents	$ per household annually
Benefits of active transport	$ per household annually

4.4.1. Car ownership costs and operation costs of public transport

Although car ownership costs are relatively small compared to the value of travel time or crashes (Barnes et al. 2004), people can make considerable savings by reducing vehicle ownership. For example, better public transport services or better conditions for walking and cycling allows 10% of households to avoid purchasing a second car and enables $1300 in savings per household annually (Litman 2003). Vehicle ownership costs can be divided into two separate categories:

1. Standing costs
    - depreciation
    - interest on loan
    - registration
    - licence
    - RACV membership
    - other on-road costs
2. Running costs
    - fuel
    - tyres
    - service/repairs

Eighty-seven per cent of the overall car ownership costs are related to standing costs (RACV 2011). According to the RACV, the average cost of owning and running a vehicle went down by 1.6% in 2010. Despite increased petrol prices, lower interest rates on vehicle loans have reduced some of the costs involved in taking out a loan. Slightly lower servicing expenses have also helped to give an overall reduction in costs associated with operating a vehicle (RACV 2011). According to industry experts, the rate of depreciation has generally fallen too (RACV 2012). The RACV provides standing and running costs for 2010, 2011, 2012 and 2013. Assuming the same growth trend as the past, average car ownership costs were estimated to be 72.18 cents per km in 2006 in Melbourne. Multiplying SLA's VKT by 72.18, car ownership costs were estimated for each SLA (Figure 4.5) (see '2006\ economic indicators-2006\ car ownership cost.xlsx' in Appendix 3).

Public transport, like private transport, has some costs for the society regarding its operations. Operation costs of buses are 39.42% of cars, and operating costs of trains are 26.90% of cars, while operating costs of trains is 1.86 times of trams (Fishman et al. 2011; VAG 2005). So operating costs of buses, trains and trams are 28.45, 19.41, 10.38 cents per passenger km, respectively.

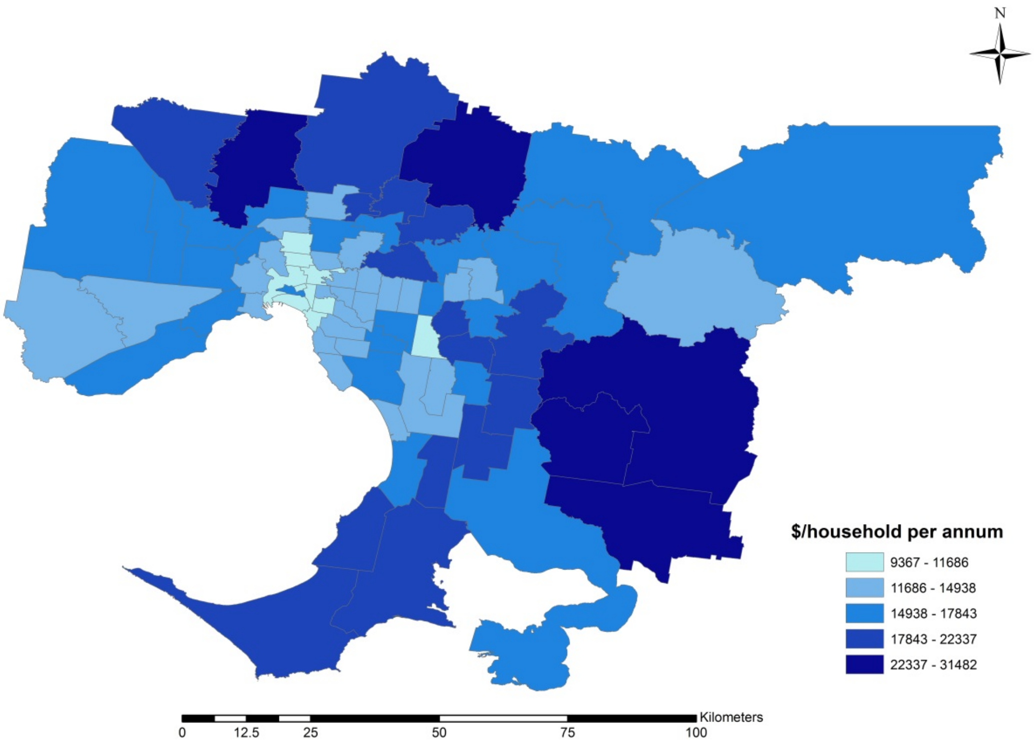


Figure 4.5. Car ownership and public transport operation costs in Melbourne (2006)

4.4.2. Accident costs

The costs of road transport accidents have two broad components: one is the human costs involving lost production related to fatalities and injuries; and the other is the material costs, which is made up of property damage, insurance administration, and a variety of other costs (Table 4.8) (BTCE 1992). A detailed description of measuring social costs related to road crashes is presented in BITRE (2009). To quantify the related costs of accidents, estimates of the number of accidents, the number and severity of vehicle damages, human injuries, disabilities and deaths are required (Litman 2009).

Economic value is assigned for premature deaths and disabilities caused by road crash injuries. Whereas a particular life may be regarded as priceless, relatively low values may be assigned to statistical lives. The value of statistical life is not the life of any particular person that is valued, but that of an unknown or statistical individual. Valuing statistical life eliminates subjective assessments (BTRE 2005). There are two common ways to measure economic costs of deaths and injuries related to accidents (BITRE 2009):

- Human-capital method: This method quantifies the value of the years of life lost due to mortality. It measures the economic impact of deaths and injuries through the loss of output or productivity. This is generally done by calculating the present value of a person's potential future output, as measured by their earnings.

- Willingness to pay method: This method estimates the financial value of life according to the amounts that individuals are prepared to pay to reduce risks to their lives. This approach uses people's preferences to measure the value they place on reducing risk to life.

Table 4.8. Major components of costs ($ millions) of road accident (BITRE 2009)

Cost element	**Human-related costs**	**Property damage and general costs**	**Total crash cost**
Workplace and household losses	5690.0	N/A	5690.0
Repair costs	0	4227.5	4227.5
Disability-related costs	1863.9	N/A	1863.9
Non-pecuniary costs	1768.0	N/A	1768.0
Insurance administration	269.7	1421.3	1691.0
Medical and related costs	864.2	N/A	864.2
Travel delay and additional vehicle operating costs	N/A	839.7	839.7
Legal costs	267.9	NSE	258.2
Vehicle unavailability costs	N/A	214.1	214.1
Other	256.5	166.5	423.0
Total	10980.2	6869.1	17849.3
N/A: not applicable NSE: not separately estimated			

BITRE (2009) estimated that the cost of human losses are approximately $2.4 million per fatality and $214 000 per injury for Australia in 2006, using the human capital method. Vehicle and general costs are 64.15% of the human costs in Victoria (Table 4.9). As the number of fatalities and injuries related to accidents was quantified as a social indicator, to avoid the double-counting, this indicator included only vehicle and general costs related to accidents (Figure 4.6) (see ‘2006\ economic indicators-2006\crash fatality and injury costs.xlsx’ in Appendix 3).

Table 4.9. Estimated cost ($ millions) of road accidents by cost type in Victoria and Australia (BITRE 2009)

Cost component		VIC	Australia
Human costs	Fatalities	817.1	3842.4
	Hospitalised injuries	1760.6	6679.5
	Non-hospitalised injuries	120.8	458.3
Vehicle and general costs		1731.1	6869.1

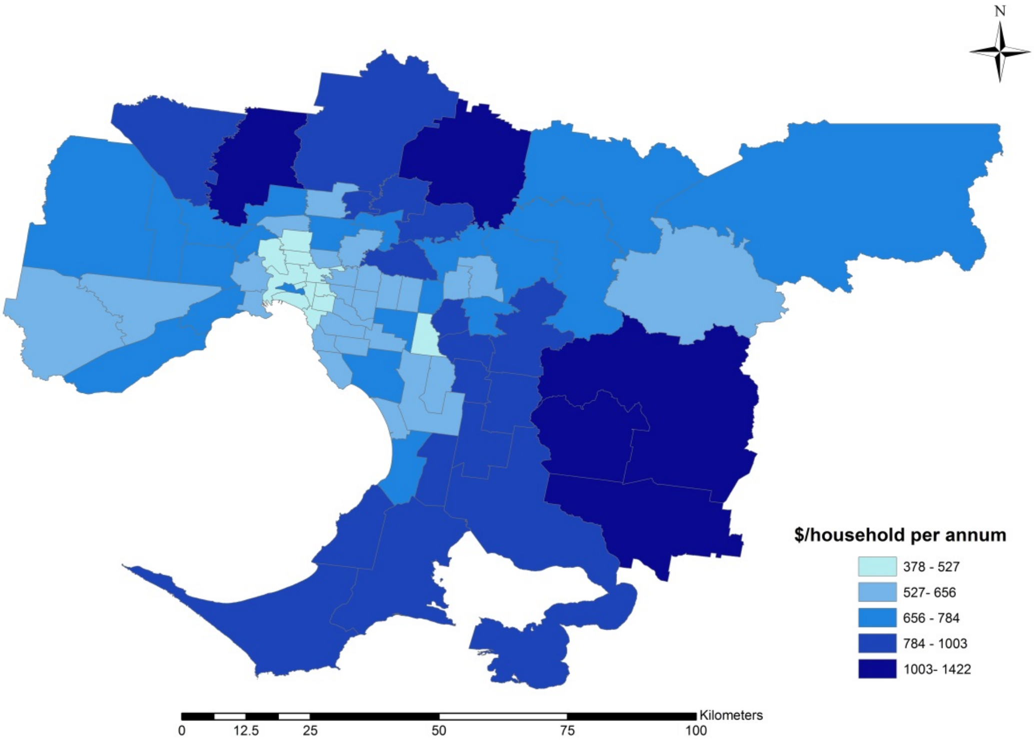


Figure 4.6. Vehicle and general costs related to accidents in Melbourne (2006)

4.4.3. Benefits of active transport

Active transport refers to walking, cycling and other forms of human-powered mobility. Walking and cycling for transport offers a range of benefits in terms of population health, greenhouse gas emissions, congestion relief and urban liveability. Analysis of the benefits of active transport requires estimates of the changes in travel behaviour, including reductions in car use and increases in active transport. Both are needed because some of the benefits relate to reduction of the negative impacts of car use while others relate to increases in the beneficial outcomes of active transport (Fishman et al. 2011).

Benefits of walking and cycling include (Fishman et al. 2011; PWC 2011):

- **Congestion savings** – a shift from motor vehicles to walking will reduce the number of vehicles and congestion and increase road speeds.
- **Road provision savings** – a decline in the motor vehicle use of roads will reduce road maintenance and construction costs.
- **Vehicle operating cost savings –** individuals may save on the costs of maintaining a vehicle, including fuel, depreciation and tyres.
- **Public transport operating costs** – where there is an impact on public transport usage.
- **External parking savings** – user parking costs, and the public cost of providing and maintaining vehicle parking facilities will be reduced.
- **Road safety** – safety is improved when separated pathways or roadway safety and awareness initiatives are implemented.
- **Environmental pollution savings** – greenhouse gas (GHG) emissions, air pollution and water pollution are reduced.
- **Noise reduction** – noise levels are reduced if more individuals walk rather than use transport, especially in residential areas where the costs of noise are high.
- **Health cost savings** – an increase in physical activity may reduce morbidity and mortality.

Although walking and cycling have many benefits, to have balance with the costs considered in this study, benefits that are in accordance with considered costs were quantified here: car ownership and public transport operation cost savings, health cost savings, and environmental pollution savings. As mention above, before estimating savings it is needed to quantify kilometres travelled by walking and cycling. Equations 4.7 and 4.8 were used to do the quantification:

$$pja = 100 - (pjc + pjp) \qquad 4.7$$

pja = percentage of trips by active transport (walking and cycling)
pjc = percentage of trips by car
pjp = percentage of trips by public transport

$$WKT = pja\,(VKT_{full} - VKT_{actual}) \qquad 4.8$$

WKT = km travel by active transport (walking and cycling)
VKT_{full} = estimated VKT for full (2cars) carownership
VKT_{actual} = estimated VKT for actual carownership

After quantifying kilometres travelled by walking and cycling, savings were quantified as follows (Figure 4.7):

- *Car ownership and public transport operation costs savings*

  Active transport causes reduction in public and private transport and consequently their operation costs. Using modal split, which was calculated in Chapter 3, the number of vehicle kilometres travelled by both public and private transport, substitute by walking and cycling, were multiplied by car ownership costs and operation costs of public transport to quantify car ownership and public operation cost savings. It was estimated that this indicator was on average 138 cents per household in 2006.

- *Saving in accident-related costs*

  It has been suggested that walking and cycling have approximately five to ten times higher risk of injury per kilometre travelled than a car. However, it has been also suggested that the benefits of increased physical activity are substantially larger than the risk of injury. According to the literature walking or cycling would save accident costs by $0.093 per km (PWC 2011). As there is not enough data available to calculate the number of deaths and injuries related to walking and cycling for Melbourne, multiplying 0.07 (equals to 0.093 in 2011) by kilometres travelled by walking and cycling, it was estimated that the health-cost savings of walking and cycling was on average 15 cents per household in 2006.

➢ *Saving costs of mortalities related to air pollutants*

As walking and cycling produce no emissions, they can reduce number of deaths related to air pollutants. After calculating the number of deaths avoided because of reduction in emissions of public and private transport (Section 4.3.3), the value of each life saved must be calculated. Bureau of Infrastructure, Transport and Regional Economics (BTRE, 2005) used a value of $1.3 million (in 2000 dollars) for estimating the cost of air pollution-related premature mortality. Considering the inflation rate, this value would be $1.56 million in 2006. Based on the analysis, $4.56 per household would be saved due to the reduction in public and private transport emissions in 2006.

Based on all the above calculations, the total benefits of walking and cycling was $424,359,230 annually for all households.

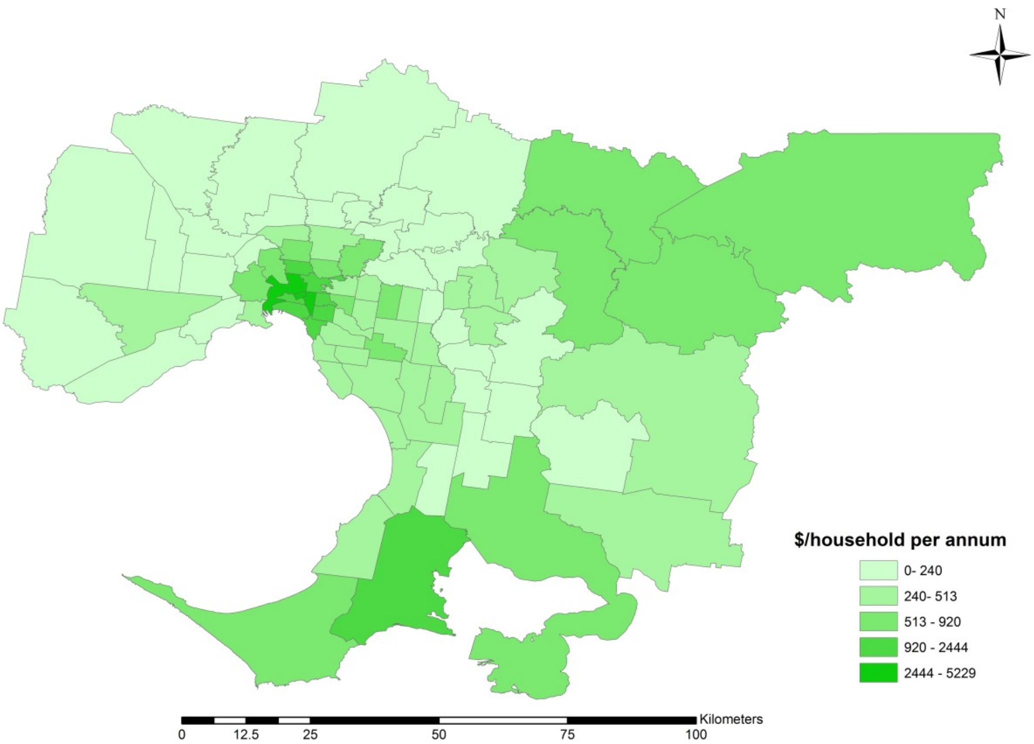


Figure 4.7. Benefits of walking and cycling (Melbourne, 2006)

4.5. Chapter summary

This chapter described the social and economic indicators selected for transport sustainability. According to indicators selection criteria and previous research on transport sustainability, accessibility, fatalities and injuries related to traffic accidents, mortality effects of air pollutants, car ownership and public transport operation costs, vehicle and general costs of accidents, and benefits of walking and cycling were selected in the current study. Different methods were used to quantify these indicators. VKT and air pollutants emissions, estimated in the previous chapter, were the essential components for quantifying selected social and economic indicators in this chapter. A comprehensive accessibility index was developed to quantify accessibility by walking and public transport. This index overcomes the limitations of other accessibility indices developed for Melbourne, which were discussed in Chapter 2.

In the next chapter, environmental, social, and economic indicators will be normalised, weighted and aggregated into transportation environmental impact index (TEII), transportation social impact index (TSII), transportation economic impact index (TCII) and then into transport sustainability index (I_{CST}).

Chapter 5

Composite Sustainable Transport Index

A list of environmental, social, and economic indicators was selected for this study based on literature review and indicators selection criteria in Chapters 3 and 4. In the next stage, selected indicators (depletion of non-renewable resources, GHG emissions, other air pollutants emissions, land consumption for transport, accessibility index, fatalities and injuries related to traffic accidents, mortality effects of air pollutants, car ownership and public transport operation costs, vehicle and general costs of accidents, and benefits of walking and cycling) were quantified using different methods. This chapter presents normalisation, weighting, and aggregation methods to create transportation environmental impact index (TEII), transportation social impact index (TSII), transportation economic impact index (TCII). These indices were aggregated for Melbourne 2006 to quantify composite sustainable transport index (I_{CST}) by using the methods presented.

5.1. Introduction

A composite index is a mathematical aggregation of a set of individual indicators that measure multi-dimensional aspects but usually do not have common units of measurement (Zhou et al. 2007). Composite indices are valuable communication and policy tools because they are able to integrate large amount of information into easily understood single number.

These single indices are valuable because they limit the number of statistics to be presented and allow for quick comparisons of an area performance (Freudenberg 2003). These characteristics are the reasons for the popularity of composite indices among stakeholders. Stakeholders are willing to summarise multitude of indicators into a single figure to assess performance of an area easily (Zhou et al. 2007).

Despite their advantages, composite indices are able to reflect the complexity of performance and policies. A simple composite index, as an average of individual indicators, is a substitute for its components (Freudenberg 2003). Although deficiencies exist in aggregated composite index, policymakers will rely on them for decision making. These indices can be useful if they are designed with transparent structures and can be disaggregated into the separate indicators and if no information is lost (Jollands 2003). Indicators normalisation and weighting must be done before aggregation, which will be described in the following sections.

5.2. Normalisation

Selected indicators have different kinds of quantitative information with different measurement units. Therefore, to avoid adding up different scales, before going to the aggregation stage, it is necessary to bring the indicators to the same scale, by transforming them into dimensionless numbers. This process is called normalisation (Nardo et al. 2005).

It must be noted that that some indicators can be considered as negative indicators (i.e. indicators whose increasing values have negative impact on sustainability) while others can be considered as positive indicators (i.e. indicators whose increasing values have positive impact on sustainability). To consider both positive and negative indicators in the final index, any normalisation process should take this distinction into account (Cherchye et al. 2004). Rescaling or min-max method which normalise indicators between the value of 0 and 1, is suitable for this study, because it can differentiate between positive and negative indicators (Krajnc et al. 2005). Equations 5.1 and 5.2 provided by Cherchye et al. (2004), were applied for indicators' normalisation. It is worth noting that 0 in the normalised indicators always corresponds to the worst performance and 1 corresponds to the best performance.

$$I_N^+ = \frac{I^+ - I_{\min}^+}{I_{\max}^+ - I_{\min}^+} \quad 5.1$$

$$I_N^- = \frac{I_{\max}^- - I^-}{I_{\max}^- - I_{\min}^-} \quad 5.2$$

Where:

I_N= Normalised indicator I

“+” = For indicator whose increasing value has positive impact on sustainability

“-”= For indicator whose increasing value has negative impact on sustainability

min = Minimum value of indicator

max = Maximum value of indicator

5.3. Weighting

Indicators which are aggregated in a composite index have first to be weighted using equal or different weights. Greater weight should be given to indicators that are more significant in the context of the particular composite index (Freudenberg 2003). This approach has drawn much criticism because it is an arbitrary process and no weighting method can justify giving a particular weight to an indicator (Tanguay et al. 2010). As mentioned in the second chapter, there are three available weighting methods: equal weighting, weighting based on opinions, and weighting based on statistical models (Saisana 2011). In many composite indices, all indicators are given the same weight for simplicity. This implies that all indicators in the composite index have equal importance, which may not be the case. With the equal weighting approach, there is a risk that certain aspects are double counted. This is because two or more indicators may be measuring the same aspect (Freudenberg 2003). Weights based on opinions or expert’s judgements are subjective and arbitrary. So statistical models are more appropriate for weighting compared to others. A discussion of major statistical weighting methods and their descriptions are provided in the following sections.

5.3.1. Data envelopment analysis (DEA)

Using mathematical programming techniques, this method compares the efficiency of chosen decision-making unit (DMU) with all possible linear combinations of other DMUs (Saisana 2011). The efficiency of each DMU can be computed by Equation 5.3:

$$Max\ h_j = \frac{\sum_{r=1}^{s} U_r Y_{rj}}{\sum_{i=1}^{m} V_i X_{ij}} \tag{5.3}$$

$h_j = \text{The efficeincy of unit } j$

$j = \text{Number of DMU}$

$r = \text{Number of outputs}$

$i = \text{Number of inputs}$

$U_r = \text{Weight given to output r}$

$Y_{rj} = \text{The amount of r}^{\text{th}} \text{ output produced by unit } j$

$V_i = \text{Weight given to input i}$

$X_{ij} = \text{The amount of i}^{\text{th}} \text{ input consumed by unit } j$

The above equation is calculated n times to identify the relative efficiency scores of all DMUs. DEA allows DMUs to select indicators weights that are the most advantageous for them in calculating their efficiency scores (Kao et al. 2005). In other words, DEA will allow the DMU to assign very high weights to the output(s) and input(s) for which the DMU is particularly efficient and very low weights to all the other inputs and outputs. As a result, the relative efficiency of a DMU may not really reflect its performance on the inputs and outputs taken as a whole (Chaparro et al. 1997). Moreover, this method of weighting deters the comparison among DMUs on a common base. Another limitation of this method is that it classifies all DMUs into two groups, efficient and inefficient, while in most cases ranking efficient and inefficient units are essential (Kao et al. 2005). The third limitation of this method is that an inefficient unit with a smaller efficiency score does not necessarily mean poorer performance than one with a larger efficiency score because only the units under the same frontier facet are comparable (Kao et al. 2005).

Another statistical weighting method is benefit of the doubt (BOD). The application of DEA to the field of composite indices is known as BOD. In this method, there is a need for a benchmark to weight indicators. A composite index of an area is not given by a weighted sum of its indicators, but rather by the ratio of this sum to sum of the benchmark indicators. This method has the same limitations as DEA. Good relative performance of an area on an indicator is given higher weight, while the lower weights are given to indicators on which the area performs relatively poor (OECD 2008).

In the case of this study, DMUs are different Melbourne SLAs, inputs and outputs are selected sustainability indicators, and efficiency is final sustainability index. Tools developed for conducting DEA analysis based on complex mathematical programming do not provide single weight for each input and output; rather they provide final efficiency (sustainability index) for each DEA. On the other hand, in this study all selected indicators are the outputs of transport systems and there are no inputs. Based on these deficiencies, DEA was not selected for indicators weighting in this study, as a common single weight for each indicator is required.

5.3.2. Principal component analysis/factor analysis (PCA/FA)

Factor analysis (FA) is based on the common factor model (Figure 5.1). In this model each observed response (Measure 1 through to Measure 5) is influenced partially by underlying common factors (Factor 1 and Factor 2) and partially by underlying unique factors (E1 through to E5). The strength of the link between each factor and each indicator (measure) varies, such that a given factor influences some measures more than others.

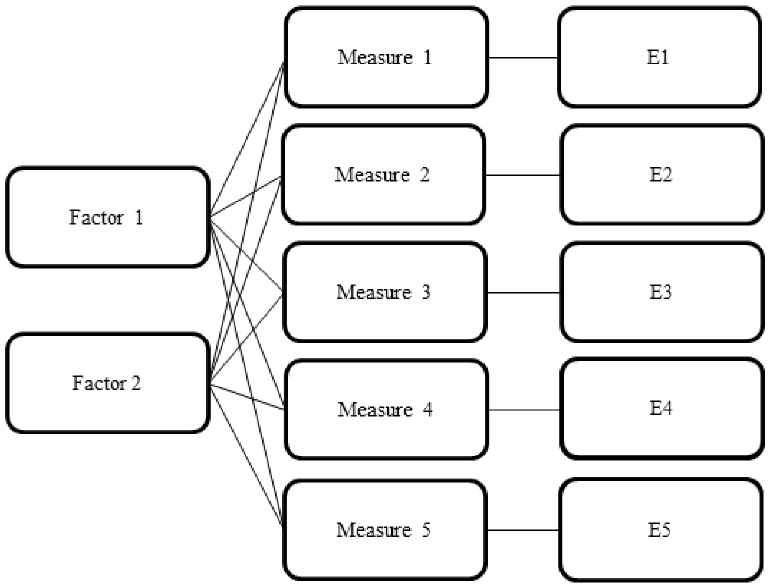


Figure 5.1. The common factor model (DeCoster 1998)

Based on the common factor model, FA groups together individual indicators which are collinear to form a composite index that captures as much as possible of the information common to individual indicators. Each factor reveals the set of indicators with which it has the strongest association. The first phase of FA is factors' extraction. PCA is a widely used method for factor extraction. After factor extraction, factors' loading must be assigned. Each factor depends on a set of coefficients (loadings), which measure the correlation between the individual indicator and the extracted factor. The purpose of using this method in the context of this study is to create weights based on each indicator contribution to the variance of the entire sample (OECD 2008). Although independency is a selection criteria for indicators used in this study, to avoid probable co-linearity among selected indicators, PCA/FA is used for weights extraction.

Before applying PCA/FA, it must be checked that the correlation among indicators is not due to redundancy of the information. To test whether PCA/FA could be applied, Kaiser-Meyer-Olkin (KMO) measure or Bartlett's test of sphericity is used. KMO is a measure of sampling adequacy. KMO measure varies from 0 to 1. A KMO measure should be 0.6 or higher for a good PCA/FA. The Bartlett test is used to test the null hypothesis that the individual indicators in a correlation matrix are uncorrelated. If the value of the Bartlett test is large and the associated significance level is small, it is unlikely that indicators in a correlation matrix are uncorrelated (OECD 2008; Saisana 2011).

The first step in PCA/FA is to check the correlation between indicators, so indicators correlation matrix is prepared first. The second step is the identification of a certain number of latent factors (fewer than the number of individual indicators) representing the data. Each factor depends on a set of coefficients (loadings); each coefficient measures the correlation between the individual indicator and the factor. Principal components analysis is usually used to extract factors. PCA considers 'p' indicators, X_1, X_2,…, X_p and find linear combinations of these to produce principal components (or factors) Z_1, Z_2, Z_3,…, Z_p that are uncorrelated (Saisana et al. 2002). Factor extraction using PCA needs two sets of values:

1. Eigenvectors is a column or row of numbers in a correlation matrix. It is a column of weights each applicable to one of the variables in the matrix. The symbol for an eigenvector is V_a.

2. Eigenvalue is shown by I_a symbol, is the sum of squares of factor loadings of each factor and reflects the proportion of variance explained by each factor. This total amount of

variance is an eigenvalue for the factor. The larger the eigenvalue the more variance is explained by the factor.

The eigenvectors and eigenvalues are derived by an iterative method. A vector is tried out and tested against an indicator set of values. To the extent that it differs from the indicator, the first trial vector is modified to produce a second vector and so on until the solution converges, i.e. until additional iterations produce virtually identical results (sum of squared differences between two eigenvectors must be less than 0.0001). In the iterative approach eigenvectors are obtained one at a time. Once the iterative solution has converged, the eigenvalue can be calculated from the vector and the same iterative method is then used to search for successive vectors. How this is actually done is described in a series of steps on a simple correlation matrix among selected environmental indicators which is given in Table 5.1 (Kline 1994).

Table 5.1. Sample correlation matrix among environmental indicators

	Depletion of non-renewable resources	**GHG emission**	**Other air pollutants**	**Land consumption for transport**
Depletion of non-renewable resources	1	1	0.996	0.638
GHG emissions	1	1	0.994	0.639
Other air pollutants	0.996	0.994	1	0.626
Land consumption for transport	0.638	0.639	0.626	1

Step 1: Sum of coefficients in each column is calculated and is called vector U_{a1}. Thus U_{a1} = (3.634, 3.633, 3.616, 2.903).

Step 2: U_{a1} is normalised by squaring and adding the column sums in U_{a1} and then divide each element by the square root of sum of square. This gives the first trial of eigenvector V_{a1}. Thus V_{a1} is (0.5259, 0.5257, 0.5232, 0.4201).

Step 3: To produce the second trial vector V_{a2}, the elements of V_{a1} are accumulatively multiplied by rows of correlation matrix to obtain a new vector U_{a2} as follows:

$0.5259\times1+0.5257\times1+0.5232\times0.996+0.4201\times0.638= 0.5259+0.5257+0.5211+0.2680=1.8407$

$0.5259\times1+0.5257\times1+0.5232\times0.994+0.4201\times0.639= 0.5259+0.5257+0.5200+0.2684=1.8400$

$0.5259 \times 0.996+0.5257 \times 0.994+0.5232 \times 1+0.4201 \times 0.626=0.5237+0.5225+0.5232+0.2629=1.832$

$0.5259 \times 0.638+0.5257 \times 0.639+0.5232 \times 0.626+0.4201 \times 1=0.3355+0.3359+0.3275+0.4201=1.419$

Step 4: The second trial eigenvector V_{a2} is produced by squaring and adding the elements of U_{a2} (3.3881+ 3.3856+ 3.3573+ 2.0135 = 12.144), and then dividing each element of U_{a2} by the square root of the sum of the squared elements (3.48). So the second trial eigenvector is V_{a2} = (0.5289, 0.5287, 0.5265, 0.4077).

Step 5: In the next step, V_{a1} and V_{a2} must be compared to see if they are almost the same or not. If the sum of squared difference between the pairs of elements in the two eigenvectors was less than 0.00001 (convergence criteria), they were assumed to be almost the same. And if convergence criteria did not meet, the iteration process continued until eigenvectors converged. The factor loadings are obtained by multiplying the elements in the first eigenvector by square root of eigenvalue I_a. Thus the first factor has been extracted (Table 5.2).

Table 5.2. The first factor

Indicators	**Factor 1**
Depletion of non-renewable resources	0.940
GHG emissions	0.938
Other air pollutants	0.943
Land consumption for transport	0.337
Eigenvalue	3.480

Step 6: The second factor is obtained in the same way as the first. Thus the eigenvectors, the eigenvalues and the factor loadings are computed as above. Trial eigenvectors are extracted until convergence occurs. However, these eigenvectors and eigenvalues are not extracted from the original matrix but from residual matrix after the first factor has been removed. To obtain the residual matrix, the loadings for the two indicators on the first factor are multiplied. This is done for all possible pairs of indicators and produces a matrix of cross products. This matrix is then subtracted element by element from the original correlation matrix and the result is the residual matrix with the first factor removed.

The number of the extracted factors is assigned based on different principals. Factors which are chosen are the ones that (i) have eigenvalues larger than one; (ii) contribute individually to the explanation of overall variance by more than 10%; and (iii) contribute cumulatively to the explanation of the overall variance by more than 60% (OECD 2008; Saisana 2011). The last step deals with the construction of the weights from the matrix of factor loadings. The weights w_{kj} are obtained from the factor loading matrix using Equation 5.4:

$$w_{kj} = \frac{\left(factor\ loading_{kj}\right)^2}{eigenvalue_j} \quad 5.4$$

$w =$ Weight of indicator
$j =$ Number of factors
$k =$ Number of indicators

5.4. Aggregation

Once factors are extracted, they need to be aggregated into a single index. To calculate a single composite index using weights extracted by PCA/FA, calculation of the intermediate sustainability indicators (ISI_j), corresponding to each of the factors is needed. This is done by calculating a weighted aggregation of indicators using Equation 5.5 provided by Gemoz-Limon & Riesgo (2008) :

$$ISI_j = \sum_{k=1}^{k=n} w_{kj} I_k \quad 5.5$$

$ISI =$ Intermediate sustianability indicator
$w =$ Weight of indicator
$I =$ Normalized indicator
$j =$ Number of factors
$k =$ Number of indicators

As mentioned above, weights of indicators were calculated using Equation 5.4. Finally sub-indices were calculated as a weighted aggregation of the intermediate sustainability indicators, using Equation 5.6 provided by Gemoz-Limon & Riesgo (2008):

$$I = \sum_{j=1}^{j=m} \alpha_j ISI_j \quad 5.6$$

$I =$ The value of sub - index
$j =$ Number of factors
$ISI =$ Intermediate sustianability indicator

α is the weight applied to the intermediate sustainability indicator. This weight was calculated using Equation 5.7:

$$\alpha_j = \frac{eigenvalue_j}{\sum_{j=1}^{j=m} eigenvalue_j} \qquad 5.7$$

In order to compare different Melbourne SLAs in terms of transport sustainability, it is necessary to build a composite index to cover all environmental, social, and economic aspects. So, first PCA/FA analyses were done for sub-indices and then sustainability sub-indices were combined into a composite sustainable transport index (I_{CST}) using Equation 5.8 provided by Gemoz-Limon &Riesgo (2008) :

$$ISS_j = \sum_{k=1}^{k=n} w_{kj} I_k \qquad 5.8$$

ISS = Intermediate sustianability sub-index
w = Weight of sub-index
I = Sub-index value
j = Number of factors
k = Number of sub-indices

The weights w_{kj} are obtained from the factor loading matrix:

$$w_{kj} = \frac{(factor\ loading_{kj})^2}{eigenvalue_j} \qquad 5.9$$

w = Weight of sub-index
j = Number of factors
k = Number of sub-indices

Finally a composite sustainable transport index (I_{CST}) was calculated as a weighted aggregation of the intermediate sustainability sub-indices:

$$I_{CST} = \sum_{j=1}^{j=m} \alpha_j ISS_j \qquad 5.10$$

I_{CST} = Composite sustiable transport index
j = Number of factors
ISS = Intermediate sustianability sub - indices

α is the weight applied to the intermediate sustainability sub-indices. This weight was calculated as follows:

$$\alpha_j = \frac{eigenvalue_j}{\sum_{j=1}^{j=m} eigenvalue_j} \qquad 5.11$$

Calculated weights for each indicators and each sub-index is shown in Table 5.3 (see '2006\final index 2006 – PCA - household level\ PCA.sav, PCA for environmental indicators.spv, PCA for social indicators.spv, PCA for economic indicators.spv, PCA for final index. sav, PCA for final index.spv' in Appendix 3).

Table 5.3. Weights of indicators based on PCA/FA

Aspect	**Kaiser-Meyer-Olkin measure**	**Indicators**	**Weights on factor 1**	**Weights on factor 2**
Environmental	0.69	Depletion of non-renewable resources	0.2539	0.2266
		GHG emissions (CO_2)	0.2528	0.2293
		Other air pollutants (CO, NO_2, PM_{10})	0.2555	0.2084
		Land Consumption for transport	0.0326	1.7260
Social	0.59	Accessibility	0.4376	0.0239
		Fatalities and injuries related to traffic accidents	0.4300	0.0371
		Mortality effects of air pollutants	0.0147	1.2213
Economic	0.55	Car ownership and public transport operation costs	0.4080	0.0779
		Vehicle and general costs of accidents	0.4047	0.0876
		Benefits of walking and cycling	0.0242	1.3885
Final index	0.70	Environmental sub-index	0.3157	0.4626
		social sub-index	0.0664	2.6855
		economic sub-index	0.2840	0.7073

Table 5.4. α calculated for each aspect of sustainability based on PCA/FA

Aspect	α for factor 1	α for factor 2
Environmental	0.8715	0.1284
Social	0.7061	0.2938
Economic	0.7735	0.2264
Final index	0.8954	0.1045

Indices created for Melbourne 2006 are shown below (see '2006\final index – PCA-household level\final environmental index.xlsx, final social index.xlsx, final economic index.xlsx, final.xlsx' in Appendix 3):

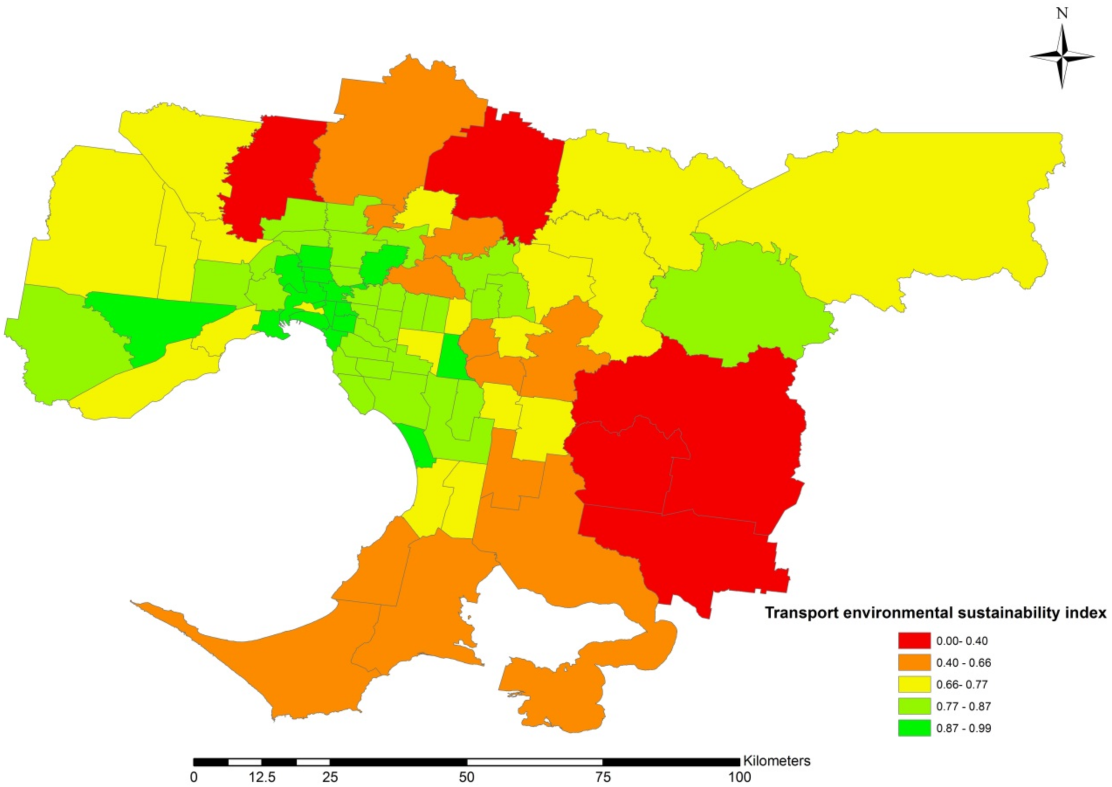


Figure 5.2.Transportation environmental impact index (TEII) in Melbourne 2006

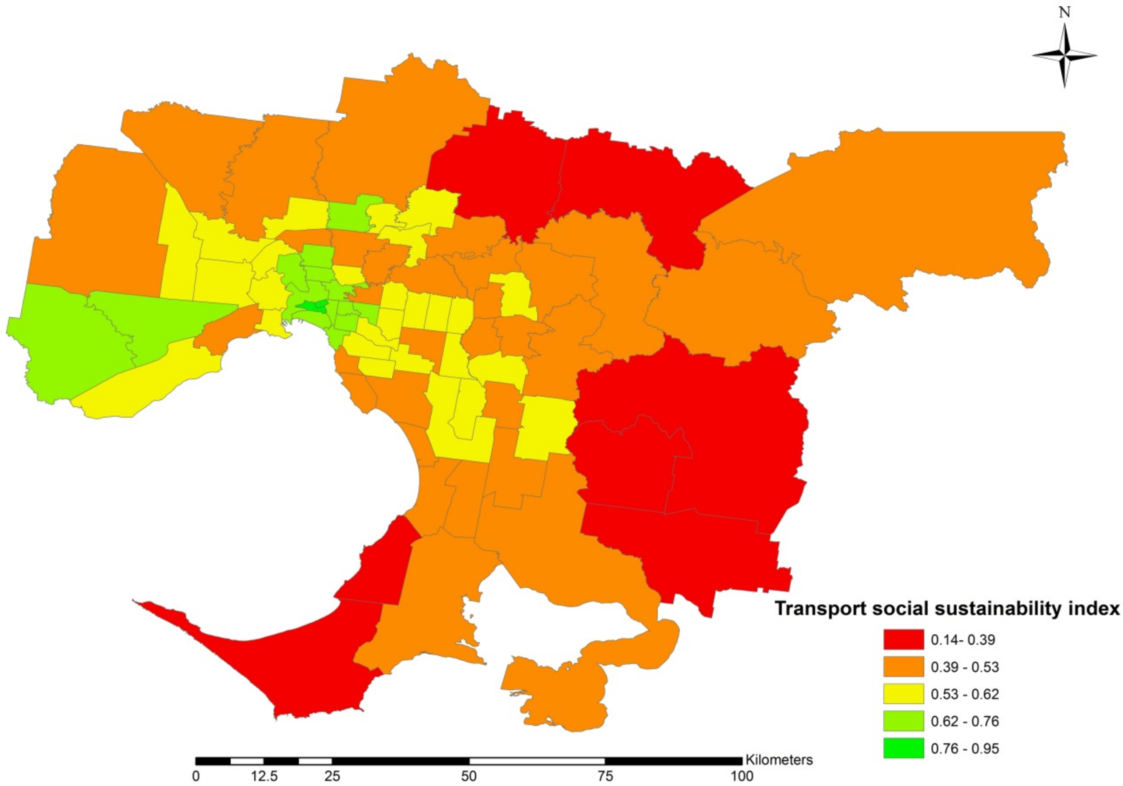


Figure 5.3. Transportation social impact index (TSII) in Melbourne 2006

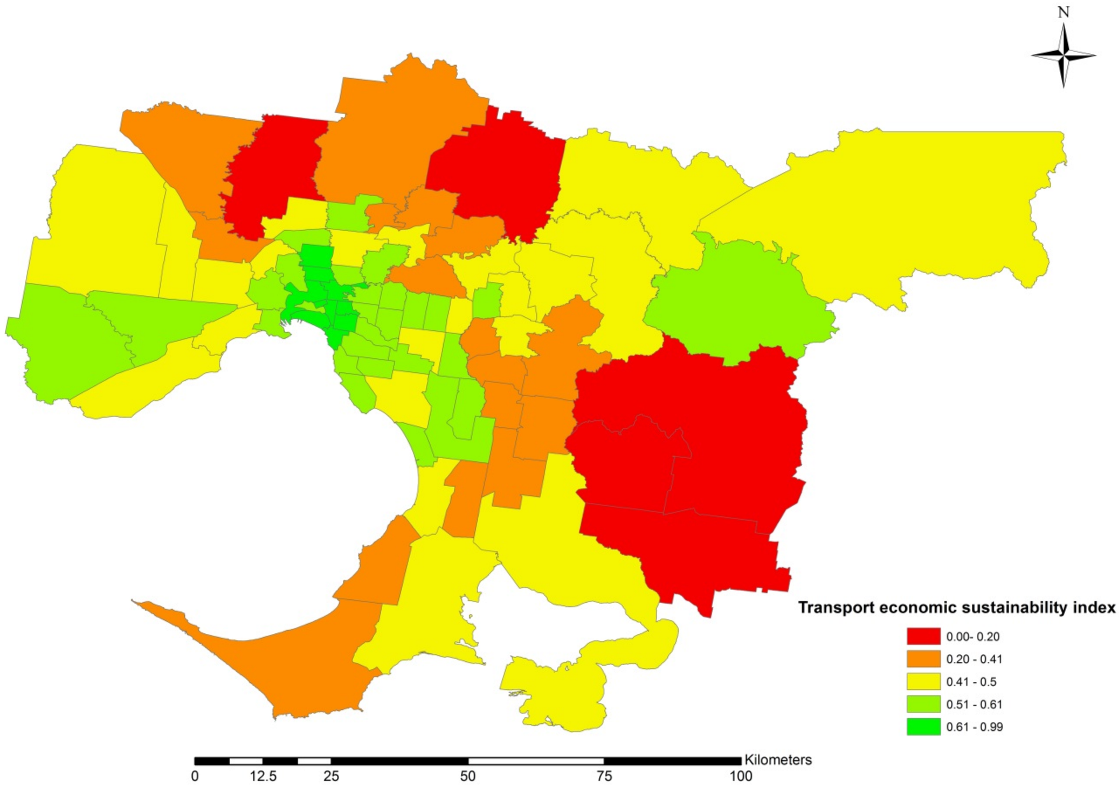


Figure 5.4.Transportation economic impact index (TCII) in Melbourne 2006

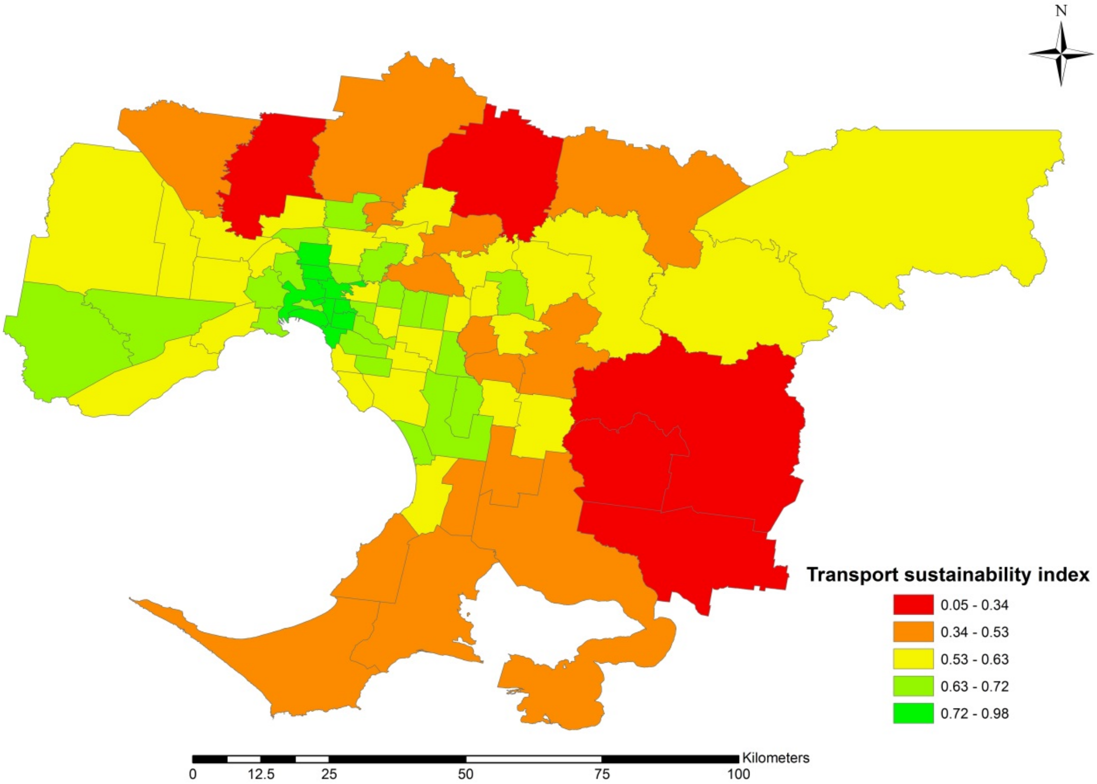
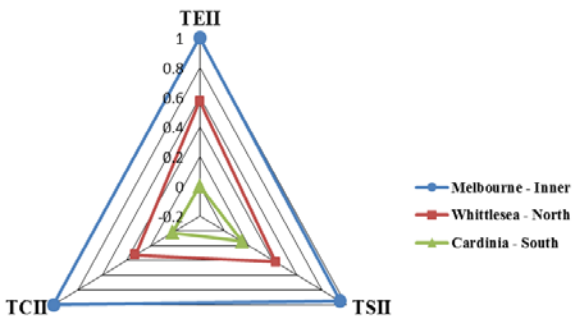


Figure 5.5. Composite sustainable transport index (I_{CST}) in Melbourne 2006

Average TEII, TSII, TCII, and I_{CST} are 0.75, 0.55, 0.49, and 0.61 for Melbourne in 2006 respectively. Three SLAs, one with the highest (Melbourne – Inner), one with the lowest (Cardinia – South) and one with medium sustainability (Whittlesea – North) in different aspects are shown in Figure 5.6. SLAs that have good sustainability in each aspect provide more overall sustainability as well. While low sustainability in environmental, social and economic aspects causes low composite sustainability.



5.5. Chapter summary

This chapter describes the approach for normalisation, weighting, and aggregation. Min – max method was used to normalise negative and positive indicators. After normalisation, different weighting methods were compared and a suitable method was selected for calculating indicators' weights. After using PCA/FA analysis for weighting, indicators were aggregated to transport environmental, social and economic impact indices. The indices were aggregated in the final stage to calculate composite transport sustainability index for Melbourne in 2006. The following chapter defines different urban-planning scenarios for 2030 and present the process of predicting selected indicators for the future. The same quantification, normalisation, weighting, and aggregation for environmental, social, economic indicators will be undertaken for different urban-planning scenarios in 2030.

Chapter 6

Scenario Development

6.1. Introduction

An important focus in land-use/transport studies is the evaluation of various urban-development scenarios. Various researchers have tried to consider how different urban-planning scenarios perform with regard to energy consumption and emissions levels. For example, Newton (1997) considered five different urban-planning scenarios and their effects on CO, VOC, NO_x, SO_2, PM_{10}, and CO_2 emissions for Melbourne in 2011. Newton (1997) suggested that a compact-city scenario (where all new urban growth is limited to the inner city) offered the best option for lowering emissions, compared to other scenarios. In another study, Trubka et al. (2008) estimated the relative costs associated with two different types of urban development, i.e. intensive inner suburban infill re-development and conventional fringe development. They found that higher-density, mixed-use inner urban areas in Sydney, Melbourne and Perth tend to have lower greenhouse gas emissions than lower-density outer suburban areas, and that the former have fewer economic costs associated with them than the latter. In another study in Sydney, Rickwood (2009) considered 16 different scenarios and their effects on dwelling and transport energy usage and emissions. He concluded that scenarios with less fringe development (and hence more redevelopment of existing areas) have better emissions outcomes. Despite attempts to investigate the effects of different urban-planning scenarios on transport energy consumption and emissions, there is no investigation about urban-planning effects on transport sustainability in the future. So the current study attempts to contribute to the pool of knowledge by quantifying transport sustainability for three different urban-planning scenarios for Melbourne in 2030.

As mentioned before, 2030 was selected in this study as the target year for all scenarios. For predicting transport sustainability in the future, all single environmental, social, and economic indicators need to be predicted. Further, as some indicators were quantified based on the land-use/transport interaction model from Chapter 3, the inputs of this model also need to be quantified. Most of the predictions used in this study were based on an urban-development plan for Melbourne. In this chapter, first a base-case scenario and its inputs are presented. Then, two other scenarios and their inputs are defined.

6.2. Base-case scenario

The base-case scenario for 2030 is based on government plans for Melbourne in that year. Melbourne 2030 – Planning for sustainable growth (DTPLI 2002), is a 30-year plan to manage growths and changes across metropolitan Melbourne and the surrounding region. The main aim of the plan is to continue to protect the liveability of established areas and to increasingly concentrate major changes in strategic re-development sites.

The base-case scenario will be the continuation of development that accords with the current planning and transport framework including, Melbourne 2030 (DTPLI 2002); Victoria in Future (DTPLI 2012); and Melbourne, let’s talk about the future (State Government Victoria 2012). These plans provide population, household and dwelling data for Melbourne between 2006 and 2031. Although the final year of these predictions is 2031, considering the annual change between 2006 and 2031, indicators were predicted for 2030 as the target year for the base-case scenario. It was also assumed that in this scenario, the current trends in employment and residential distribution, and the current road and public transport infrastructure provision would continue in the future.

Before predicting indicators for the base-case scenario, the factors that were used to quantify selected indicators (discussed in Chapters 3 and 4, such as the land-use/transport interaction model inputs) will be predicted in the following sections. These factors are population density, household type, household income, dwelling type, distance to nearest public transport, accessibility by public transport, and walkability.

6.2.1. Population density

Population density in 2030 was estimated based on projections by the Department of Transport, Planning and Local Infrastructure (DTPLI) for Victoria (DTPLI 2012). DTPLI uses Australian Bureau of Statistics (ABS) assumptions (Table 6.1) and the latest ABS published statistics considered births, deaths, and migration to project the population in 2030. Population projections are estimates of future population if the current demographic, economic and social trends continue.

Table 6.1. Assumptions applied by DTPLI for Victoria (2011–2031)

Parameter	Assumption
Fertility (births) rate	Total fertility rate (average number of children born to a woman over a lifetime) gradually decreases from 1.77 to 1.68.
Life expectancy	Life expectancy gradually increases to 85 years for males and 88 years for females.
Net overseas migration	18,0000 people per year to Australia, of which 27% will settle in Victoria.
Net interstate migration	Zero per year (annual interstate in-migration will equal out-migration).

Within Melbourne, the greatest population change is expected to be in the municipalities containing the designed growth areas (Cardinia, Casey, Hume, Melton, Mitchell, Whittlesea, and Wyndham). In addition to these locations, all municipalities within the existing area of Melbourne are expected to increase in population, with the strongest change in the inner areas. According to the DTPLI projection, Melbourne's population will be 6,776,164 by 2030. For calculating population density, the population is divided by area size of SLAs that are fixed over time (see 'base-case scenario – Victoria plan\population density\ population density-baseline 2030.xls' in Appendix 3).

6.2.2. Household type

A household refers to a group of two or more people usually residing in the same dwelling who make shared provisions for food and other essentials for living, or one person who makes his or her own provision for food and other essentials for living (ABS 2010). There are four different household types, as defined in Table 6.2. These definitions are provided by ABS (2010).

Table 6.2. Household types definitions (ABS 2010)

Household type	Definition
A couple family with children	Consists of two persons who are in a registered or de facto marriage, and one or more children (of any age) who usually reside in the same dwelling.
A couple family without children	Contains two persons who are in a registered or de facto marriage who live in the same dwelling where no children of any age reside.
One parent family	Consists of a person who has no spouse or partner present in the dwelling but who forms a parent-child relationship with at least one child usually residing in the dwelling.
Other families	Related individuals living in the same dwelling, however do not form a couple or parent-child relationship with any other householder, and are not attached to a couple or lone parent family. For example, a household consisting of a brother and sister only.

In order to evaluate travel behaviour in 2030, the number of households in each type must be specified, as they are needed for the land-use/transport interaction model. The mix of households in 2030 is based on population and household projection by DTPLI. Household growth is an outcome of population growth and is also related to the age structure of the population, parenting and de-parenting trends, the age at which children leave the parental home, and other socio-cultural factors. Based on the current trend in age structure and household formation, the rate of household growth will exceed population growth in Melbourne. This faster growth is associated with a decrease in the average household size. As the population changes, the living arrangements and household structures of Melbournians are also projected to change. For example, an older population leads to a greater proportion of lone person and couple-only households. While these factors change over time, the direction of change in the near future is unclear. For this reason, DTPLI projected household formation by maintaining the living arrangement probabilities (by age and gender) as of the 2006 census and applied these to the future population. This allows only the size and age of the population to influence household formation (DTPLI 2012) (see 'base case scenario – Victoria plan\ household type\household type-baseline2030.xls' in Appendix 3).

6.2.3. Household income

Household income is a key variable known to affect car ownership, vehicle kilometres travelled (VKT), and transport modal split. Thus, for a model that aims to project transport energy consumption and emissions in 2030, household income in 2030 must be projected. There is no publicly available forecast data for household income in 2030. In the absence of such projections, household annual income was projected using the household income trend between 2004 and 2007 for Melbourne's SLAs using ABS census data. Time series forecast was used to predict income in the future, using SPSS software which gives the ability to choose the best forecasting model for each time series. Moreover, by forcing the model to make predictions for points already known, we get an idea of how well the model performs. The model that was used for income prediction had an R^2 of 0.97, which shows the high-predictive ability of the model. R^2 is an estimate of the proportion of the total variation in the series that is explained by the model (*SPSS Forecasting 17.0*) (see 'base case scenario – Victoria plan\household income\income-baseline2030.xls, forecast for personal income.sav' in Appendix 3).

6.2.4. Dwelling type

There are three different dwelling types, as defined by ABS (2010) (Table 6.3). As discussed in Chapter 3, dwelling type is an effective factor of car ownership. Dwelling numbers were projected by DTPLI (2012). DTPLI used a combination of trend analysis, and ongoing consultation with local authorities to determine the most likely locations of future dwelling construction (see 'base case scenario – Victoria plan\dwelling type\dwelling type-baseline scenario 2030.xls' in Appendix 3).

Table 6.3. Definition of dwelling types (ABS 2010)

Dwelling type	Definition
Separate house	This is a house which is separated from other dwellings by at least half a metre.
Semi-detached house	These dwellings have their own private grounds and no other dwelling above or below them. They are either attached in some structural way to one or more dwellings or are separated from neighbouring dwellings by less than half a metre.
Flat, unit, or apartment	This category includes all dwellings in blocks of flats, units or apartments. These dwellings do not have their own private grounds and usually share a common entrance foyer or stairwell.

6.2.5. Distance to nearest public transport and accessibility by public transport

In predicting public transport accessibility in 2030, the City of Melbourne (2011) referred to the study by Scheurer (2010). A tool, known as SNAMUTS (Spatial Network Analysis for Multimodal Urban Transport Systems), has been developed by Scheurer to investigate the strengths and weaknesses of public transport and to build scenarios for the future that help decisions about where to add and improve public transport infrastructure and services. SNAMUTS uses two performance measures: the number of services (buses, trams or train) required to operate simultaneously on the network at the minimum service standard (service intensity), and the proportion of residents and jobs within walking distance from the minimum-standard public transport services (network coverage). Moreover, SNAMUTS quantified six separate indicators that capture different aspects of spatial accessibility and then integrated them into a composite index. These indicators are: closeness centrality, which describes the ease of movement along the public transport network in terms of speed and service frequency; degree centrality, which describes the directness of journeys along the public transport network; contour catchments, which determines the number of residents and jobs within the walkable catchment areas of activity nodes; speed comparison, which determines the travel time ratio between public transport and road travel; betweenness centrality, which captures the geographical distribution of attractive travel paths between each pair of nodes across the network; and nodal connectivity, which measures the strength of each activity node for multimodal integration of services. After developing a composite index for 2010 (current situation), composite indices were developed for future scenarios in 2030. A brief outline of the scenarios (Scheurer 2010) is presented in the following:

- *The Frequency Boost scenario*: This scenario improves and harmonises service frequencies across Melbourne public transport network. It aims to provide 10 min services (or better) on all tram routes, nearly all double tracked rail lines and a range of bus routes. The inclusion of more routes at the minimum service standard produces a larger and more connected network, and thus would increase the network coverage from 45% to 59%. The SNAMUTS composite accessibility index would improve from an average of 14.5 to 16.2 in the Frequency Boost scenario.

- *Scenarios for Surface Travel Time Reduction*: The travel time reduction scenarios address Melbourne surface public transport modes, trams and buses, and aims to speed up their operations by a mix of traffic priority measures, and operational and design improvements. In these scenarios, network coverage would not change compared to

2010. The SNAMUTS composite accessibility index would increase from an average of 14.5 to 15.0 with 15% travel time reductions and 15.4 with 25% reductions.

- *Connectivity Boost scenario*: This scenario aims to overcome a relative lack of physical integration between trains, trams and buses in Melbourne public transport network by pursuing interventions in strategic activity nodes across the metropolitan area. Network coverage will improve from 45% to 45.5%. The SNAMUTS composite accessibility index would increase slightly from 14.5 to 14.8 in this scenario.

- *The Metro Stage 1 scenario*: This scenario assesses the impact of the first stage of the proposed Metro rail tunnel between Footscray and the Domain, in combination with a boost to the frequency and coverage of the suburban rail branches (to Sydenham-Sunbury and Melton) that link into it. The scenario also contains a range of bus and tram network adaptations, particularly in the CBD area and the southern CBD fringe (where some trams are diverted to reduce the number of services parallel to the new rail tunnel) and in the outer north-western suburbs (where orbital and feeder buses are added). The suburban rail and bus extensions would expand network coverage from 45% to 46.4% of all residents and jobs. The composite accessibility index in the Metro Stage 1 scenario would have a slight drop from 14.5 to 14.4.

- *2030 Target scenario*: This scenario is based on the best-performing combination scenario (including the frequency boost, connectivity boost, and a 25% travel time reduction on surface routes), while adding a number of infrastructure projects. These include the full Metro rail tunnel from Footscray/Kensington to Caulfield/Carnegie, as well as suburban rail extensions to Wyndham Vale, Melton, Mernda, Doncaster-Ringwood, Rowville and Carnegie-Chadstone-East Malvern. Five new cross-town tram routes, two new and four extended orbital bus routes, and a Bus Rapid Transit line in the outer north are designed to add up to a benchmark for network performance that appears achievable within a 20-year time frame if the associated capital investment becomes a prime political priority. Network coverage would improve from 45% to 60.6%, while the composite index would change from 14.5 to 19.8.

The results of the 2030 Target scenario in Scheurer (2010) were used to estimate the nearest distance to public transport and accessibility by public transport in 2030. Changes in network coverage, which describe the proportion of all residents and jobs located within walking distance from public transport services, was used as changes to nearest distance to public transport in this study. Since reduction in the nearest distance to public transport increases the proportion of all residents and jobs located within walking distance from public transport services. Changes in the composite index were also used as changes to accessibility by public transport in this study (see 'base case scenario – Victoria plan\distance to nearest public transport\distance to nearest public transport - baseline2030.xls' and 'base case scenario –Victoria plan\accessibility by public transport.xls, SLA accessibility by public transport based on CCD1.xls' in Appendix 3).

6.2.6. Walkability

The Victorian Government proposed a '20-minute city' model for Melbourne walkability in the future. The model is considered in three levels, as follows:

- Neighbourhood scale, where 95% of Melbourne residents live within a 1 km walking catchment of basic day-to-day services, including healthy food options, primary schools, cafés, doctors or pharmacies, and high quality open spaces. Other services and employment are also desirable, but some will not always be feasible on the neighbourhood scale.

- Higher order services (such as health and education) should be available at major centres within 20 minutes by walking and/or public transport (including walk, wait, and travel time). These centres should be designed with a 1.6 km radius high quality walking environment.

- The CBD, to be a 20 minute public transport trip from most major suburban centres.

At all levels, the '20-minute city' should be planned with the needs of seniors and children in mind. If the city is designed around those groups, it can be expected to support all citizens. Although a healthy adult is likely to be able to walk about 1.6 km in 20 minutes, the neighbourhood centre should be based on a 1 km walking radius to support seniors and children (State Government Victoria 2012).

To estimate walkability in 2030, distances to business, education, parks, and health facilities will improve to 1 km, and then walkability is estimated using the method described in Chapter 4. Moreover, distance to public transport, which is essential for calculating walkability, was projected in Section 6.2.5 of this chapter (see 'base case scenario – Victoria plan\walkability\SLA walkability base on CCD 2030.xls' in Appendix 3).

After predicting effective factors for the land-use/transport interaction model, other environmental, social and economic indicators need to be predicted for 2030.

6.2.7. Accessibility index

Considering changes in walkability and access by public transport based on the above sections, an accessibility index was quantified for 2030 using the process described in Chapter 4 (see 'base case scenario – Victoria plan\accessibility index\accessibility index 2030.xls' in Appendix 3).

6.2.8. Land consumption for transport

There is no information available about land consumption for transport in the future. To predict this indicator for 2030, it was assumed that the road area per capita is constant over time. So by considering population growth in 2030, this indicator was estimated for 2030 (see 'base case scenario – Victoria plan\land consumption for transport\land consumption for roads.xls' in Appendix 3).

6.2.9. Fatalities and injuries related to traffic accidents

The Australian Transport Safety Bureau (ATSB 2007) has provided the road crash casualties between 1925 and 2005. Considering the changes between these years, there would be 0.28 deaths and 15.84 serious injuries per 100 million vehicle kilometres travelled in 2030 (see 'base case scenario – Victoria plan\crash fatalities and injuries\death and injuries related to accident 2030.xls' in Appendix 3).

6.2.10. Mortality effects of air pollutants

Based on Equations 4.4 and 4.5 presented in Chapter 4, the population in 2030 and the number of deaths in 2030 are needed to estimate the expected number of deaths due to air pollutants. As mentioned before in Section 6.2.1, population density in 2030 was estimated based on the population projection by DTPLI. There was no projection available for mortality in Melbourne in 2030. The City of Melbourne (2013) estimated the death rate based on historical data for Melbourne published by the ABS, and then extrapolated it into the future. Using the same method, ABS census information about the number of deaths in Melbourne between 2006 and 2011 were used in this study to estimate the number of deaths in Melbourne in 2030 and the number of deaths related to air pollutants (see 'base case scenario – Victoria plan\death\death2030.xls, death due to pm10.xls' in Appendix 3).

6.2.11. Car ownership costs and operation costs of public transport

The Royal Automobile Club of Victoria (RACV) provides standing and running costs for 2010, 2011, 2012 and 2013. Assuming the same growth trend as the past, average car ownership is estimated to be 56.70 cents per km in 2030 in Melbourne. As mentioned before in Chapter 4, operation costs of buses are 39.42% of cars, and operating costs of trains are 26.90% of cars, while operating costs of trains is 1.86 times of trams (Fishman et al. 2011; VAG 2005). So bus operation costs would be 22.35 cents per passenger km, train operation costs would be 15.25 cents per passenger km, and tram operation costs would be 8.15 cents per passenger km in 2030.

6.2.12. Accident costs

In 1996, the average cost of a fatal crash was $1.7 million and the average cost of a serious injury crash was $408,000 (BTE 2000). While in 2006, the average cost of a fatal crash was $2.67 million and the average costs of a serious injury crash was approximately $266,000 (BITRE 2009). Using the same annual growth rate, the average cost of a fatal crash will be $10.11 million and the average cost of a serious injury crash will be $113,672 for Australia in 2030.

On the other hand, in 1996, the average cost of a fatality was $1.5 million and the average cost of a serious injury was $325,000 (BTE 2000). While in 2006, the average cost of a fatality was $2.4 million and the average cost of a serious injury was approximately $214,000 (BITRE 2009). Using the same annual growth rate, the average cost of a fatality will be $9.71 million and the average cost of a serious injury will be $92,940 for Australia in 2030.

In 1996, vehicle and general costs were 78.30% of human costs; while in 2006, vehicle and general costs were 62.55% of human costs in Australia (BTE 2000) (Table 6.4). Assuming the same trend of changes, vehicle and general costs will be 38.37% of human costs in 2030 in Victoria (see 'base case scenario – Victoria plan\crash costs\crash fatalities and injuries costs 2030.xls' in Appendix 3).

Table 6.4. Costs of road crashes in Australia by costs elements ($ millions) (BTE 2000)

	1996 (millions $)	**2006 (millions $)**
Human costs of accidents	8,385	10,980.2
Vehicle and general costs of accidents	6,569	6,869.1
Total costs of accidents	14,980	17,849.3

6.2.13. Benefits of walking and cycling

As mentioned earlier in Chapter 4, using walking and cycling as a mode of transport results in savings in car ownership and public transport operation costs, as well as costs related to accidents and air pollutants. Savings related to car ownership costs, public transport operation costs, and accidents costs were quantified using the methods presented in the above sections. To quantify costs of mortalities related to air pollutants, using costs of air pollution-related mortality in 2000 and 2006 ($1.3 million and $1.56 million, respectively) (BTRE 2005) and assuming the same growth rate in the future, the costs of air pollution-related mortality was predicted to be $3.01 million in 2030.

To summarise the data presented in Section 6.2, the values of all the inputs for 2006 and the base-case scenario are presented in Table 6.5.

Table 6.5. Inputs of the base-case scenario

	2006	**2030**
Population	3,843,242	6,492,680
Household type	Couples with children: 458,458 Couples without children: 324,551 One parent families: 147,497 Other households: 21,618	Couples with children: 551,254 Couples without children: 581,273 One parent families: 247,642 Other households: 27,742
Average household annual income ($)	57,986	146,311
Dwelling type	Detached dwellings: 981,075 Semi-detached dwellings: 154,422 Flats:218,135 Others: 372,557	Detached dwellings: 1,696,839 Semi-detached dwellings: 227,082 Flats:348,186 Others: 605,076
Distance to nearest public transport (km)	1.45	0.95
Accessibility by public transport (-)	0.30	0.46
Walkability (-)	0.38	0.49
Accessibility index (-)	0.34	0.48
Land consumption for transport (km^2)	169.93	382.07
Car ownership costs (cents/km)	72.18	56.70
Fatalities and injuries related to traffic accidents	Deaths: 0.76 Injuries:14.84	Deaths: 0.28 Injuries:15.84
Mortality effects of air pollutants (number of deaths)	71.58	156.45
Accident costs ($)	Fatal accidents: 2,670,000 Injury accidents:266,000	Fatal accidents: 10,113,255.96 Injury accidents:113,672.34
Costs of air pollution-related mortality ($)	1.56 million	3.01 million

6.3. Activity-centres scenario

One of the directions of the Melbourne 2030 plan is building a more compact city (DTPLI 2002). The compact city model of urban development dates back to the 1960s, as a reaction to unlimited urban sprawl in many cities of the developed world. The proponents of the compact city model claim that higher population concentrations would bring a significant shift away from use of the private motor vehicle, toward other means of transport. The reason is that people in higher-density cities would tend to live and work in closer proximity to public transport services such as trams, trains and buses, rather than live in an outer, lower-density suburbs where distances to available public transports might be greater (Alford et al. 2008).

Based on a compact city plan, Melbourne 2030 encourages the concentration of new development at activity centres near current infrastructures. Activity centres will be built up as a focus for high-quality development, activity and living for the whole community. A substantial proportion of new housing in or close to activity centres and other strategic redevelopment sites will offer good access to services and transport. Activity centres will be the focus of major changes in metropolitan Melbourne over the next 30 years. They are uniquely placed to provide for much of the anticipated growth in households. They are, or will be, well-served by public transport, and they offer a wide range of services and facilities benefiting the whole community. This will discourage developments outside the activity centres, and will discourage continued growth at centres that cannot meet performance standards for public transport accessibility and other criteria. Metropolitan Melbourne has a network of about 100 principal and major activity centres (Figure 6.1). Each principal activity centre can serve as a focus for a range of government and community facilities and services. Major activity centres have similar characteristics to principal activity centres but serve smaller catchment areas. Continued development at major activity centres supplements the network of principal activity centres and provides additional scope to accommodate ongoing investments and changes in retail, office, service, and residential areas (DTPLI 2002).

The activity-centre scenario assumes that the provisions from government for 2030 (i.e. Melbourne 2030 (DTPLI 2002), Melbourne, let's talk about the future (State Government Victoria 2012), Victoria in Future (DTPLI 2012) will be exceeded in the principal and major activity centres. In scenario planning, planners have control on some factors, while they do not have control on others. Socio-economic factors, such as population, household type, and household income, are not under control of planners. So, factors that were modified in this scenario, compared to the base case were: dwelling types, distance to nearest public transport, walkability, and land consumption for transport. In this scenario, it was assumed that Melbourne activity centres would have 40% more apartments, and 40% less land would be devoted to transport in 2030 compared to the base-case scenario. It was also assumed that activity centres would be 40% nearer to public transport stations and walkability would increase by 40% compared to the base-case scenario (Table 6.6).

Figure 6.1. Principal and major activity centres in Melbourne (DTPLI 2002)

Table 6.6. Inputs of activity-centres scenario

Inputs	Note
Dwelling types	Apartments: 40% more than the base-case scenario in activity centres
Distance to public transport	40% less distance than the base-case scenario in activity centres
Walkability	40% more than the base-case scenario in activity centres
Land consumption for transport	40% less than the base-case scenario in activity centres

6.4. Fringe-focus scenario

This scenario assumes that all developments would be directed towards the green wedges (fringe) in 2030. This model may be defined by a belief in the advantages of spatially larger, more decentralised cities that are characterised by suburban, low-density residential living and extended road networks, which were rooted in the early 20th century (Alford et al. 2008). The 12 non-urban areas that surround the built-up urban areas of metropolitan Melbourne and are outside the urban growth boundary are known as green wedges. The green wedges accommodate agricultural and recreational uses, as well as a variety of important functions that support Melbourne. These include major assets such as airports, sewage plants, quarries and waste disposal sites; uses that support urban activity but which cannot be located among normal urban development. Based on the Melbourne 2030 plan, settlements in these areas will be allowed to expand only to the extent indicated in current Municipal Strategic Statements. This scenario assumes continued growth in the fringe until 2030, without limitations. Inputs of this scenario compared to the base-case scenario are presented in Table 6.7.

Table 6.7. Inputs of fringe-focus scenario

Inputs	Note
Dwelling types	Detached houses: 40% more than the base-case scenario in green wedges, apartments: 40% less than the base-case scenario in activity centres
Distance to public transport	40% less distance than the base-case scenario in green wedges, 40% more distance than the base-case scenario in activity centres
Walkability	40% more than the base-case scenario in green wedges, 40% less than the base-case scenario in activity centres
Land consumption for transport	40% more than the base-case scenario in green wedges

Figure 6.2. Green wedges in Melbourne (DTPLI 2002)

6.5. Chapter summary

This chapter focuses on future predictions for three different scenarios for Melbourne in 2030, as a target year for the future. A base-case scenario, an activity-centres scenario, and a fringe-focus scenario were described in this chapter. Base-case scenario is the continuation of development that accords with the current planning and transport framework including Melbourne 2030, while the activity-centres scenario and the fringe-focus scenario emphasises future developments on activity centres and the urban fringe, respectively. Victoria in Future (DTPLI 2012) is the base for most of the predictions made in this study. Where specific projections were not available for the study area, the trend analysis was used. After predicting inputs for the land-use/transport interaction model, VKT, car ownership, modal split, and consequently amount of crude oil consumed and air pollutants emissions can be predicted for

2030, which will be the focus of Chapter 7. Chapter 7 will also provide the methodology for predicting environmental, social and economic indicators, rather than transport energy consumption and emissions.

Chapter 7

Scenarios Analyses and Results

7.1. Introduction

Chapter 6 presented inputs that are required for the analysis of different scenarios. Using the inputs and land-use/transport interaction model presented in Chapter 3, transport primary fuel consumption, emissions and other environmental, social, and economic indicators are evaluated for three different urban-planning scenarios in this chapter. As mentioned in Chapter 6, base-case scenario, activity-centres scenario, and fringe-focus scenario were based on government plans for Melbourne development in 2030. The base-case scenario is the continuation of development that accords with the current planning and transport framework including Melbourne 2030 (DTPLI 2002), Victoria in future (DTPLI 2012), Let's talk about the future (State Government Victoria 2012). Activity-centres and fringe-focus scenarios encourage urban development in defined principal and major activity centres and urban fringe, respectively. A large number of figures were produced as part of the evaluation and analysis of each scenario. Presenting all of these figures for each scenario is impractical, so only limited numbers of distinct figures are presented in this chapter.

7.2. Developed scenarios

- ***Scenario 1: Base-case scenario***

  Base-case scenario for 2030 is based on government plans for Melbourne in 2030 and represents a plausible future scenario against which results for other scenarios were compared. This scenario assumed that the current urban and transport-planning framework will continue into the future.

- ***Scenario 2: Activity-centres scenario***

  As mentioned earlier in Chapter 6, in this scenario it was assumed that Melbourne activity centres would have 40% more apartments and units, and 40% less land would be devoted to transport in 2030 compared to the base-case scenario. It was also assumed that activity centres would be 40% closer to public transport stations and walkability would increase by 40% compared to the base-case scenario. This scenario represents a further strengthening of the centres already adopted in the base-case scenario. As a result of these improvements, car ownership, VKT, and proportion of car usage for travel reduce in the activity-centres scenario compared to the base-case scenario (Figure 7.1, 7.2, 7.3) (see 'activity centre scenario-2030\ car ownership-NN\ car ownership output.xlsx, VKT-NN\VKT output.xlsx, mode share-NN\mode output' in Appendix 3).

- ***Scenario 3: Fringe-focus scenario***

  To contrast with Scenario 2, which has increased activity-centres development, this scenario represents the case where there is 40% more: detached houses; access to public transport; walkability; and land devoted to transport in the fringe. Moreover, there is 40% less development in activity centres compared to the base-case scenario. These improvements result in slight increase car ownership, VKT, and proportion of car usage in the fringe-focus scenario (Figure 7.1, 7.2, 7.3) (see 'fringe scenario 2030\ car ownership-NN\car ownership output.xlsx, VKT-NN\VKT output.xlsx, modal-NN\ modal output 'in Appendix 3).

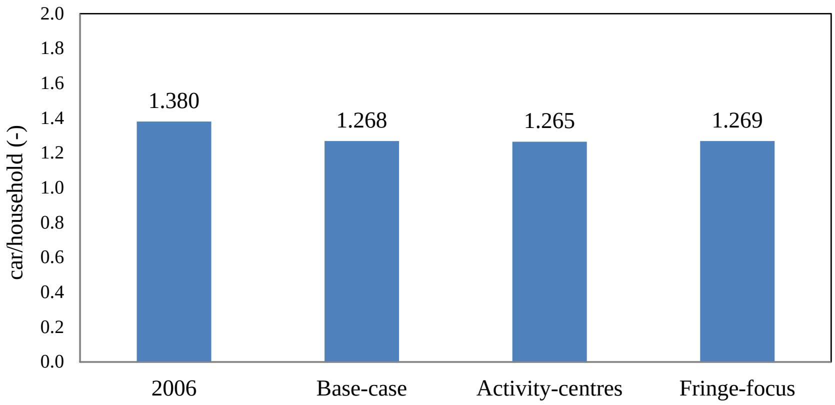


Figure 7.1. Car ownership per household for different scenarios

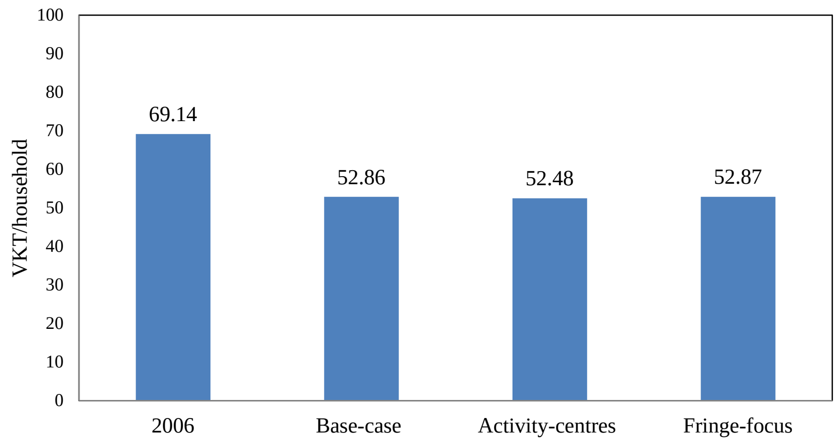


Figure 7.2. VKT (km) per household for different scenarios

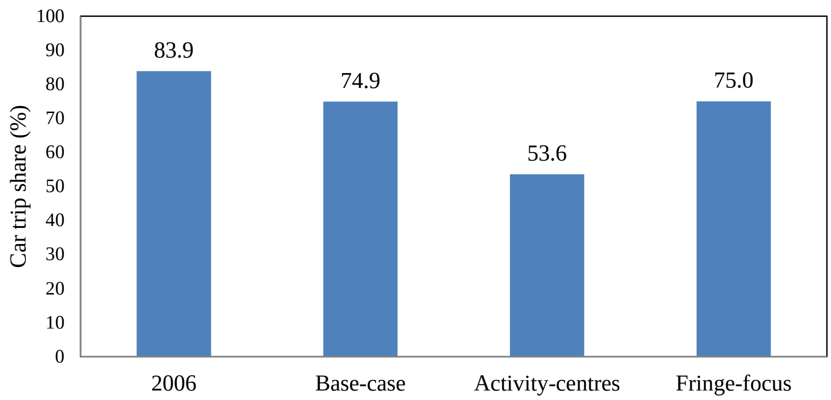


Figure 7.3. Percentage of trip by car (%) for different scenario

Environmental, social, and economic indicators quantified for each scenario will be presented in the next section. The final transport sustainability index will be presented at the end of this chapter.

7.3. Environmental indicators

Depletion of non-renewable resources, air pollutants emissions, and land consumption for transport were quantified for each scenario using methods described in Chapter 3, and inputs predicted for each scenario in Chapter 6.

7.3.1. Depletion of non-renewable resources

- ***Base-case scenario***

  Land-use and socio-economic factors were predicted for the base-case scenario in Chapter 6. Using these factors, car ownership, VKT, and modal split were predicted for the scenario using the land-use/transport interaction model (Chapter 3). Using VKT, car ownership, and modal split, it was projected that households would consume 1.287E+11 MJ energy per year, which is equivalent to 3.67E+09 litres of primary fuel (crude oil). The average annual figures per household would be 93892 MJ and 2679 litres respectively (Figure 7.4). Although per household figures represents a 9.8% reduction in energy and primary fuel consumption compared to 2006, due to household number increase (from 946,107 to 1,403,852), total energy and primary fuel consumption for all households would increase by 33% (Figure 7.5) (see 'base case scenario-Victoria plan\ environmental indicators\resource depletion-crudeoil-base2030.xlsx' in Appendix 3).

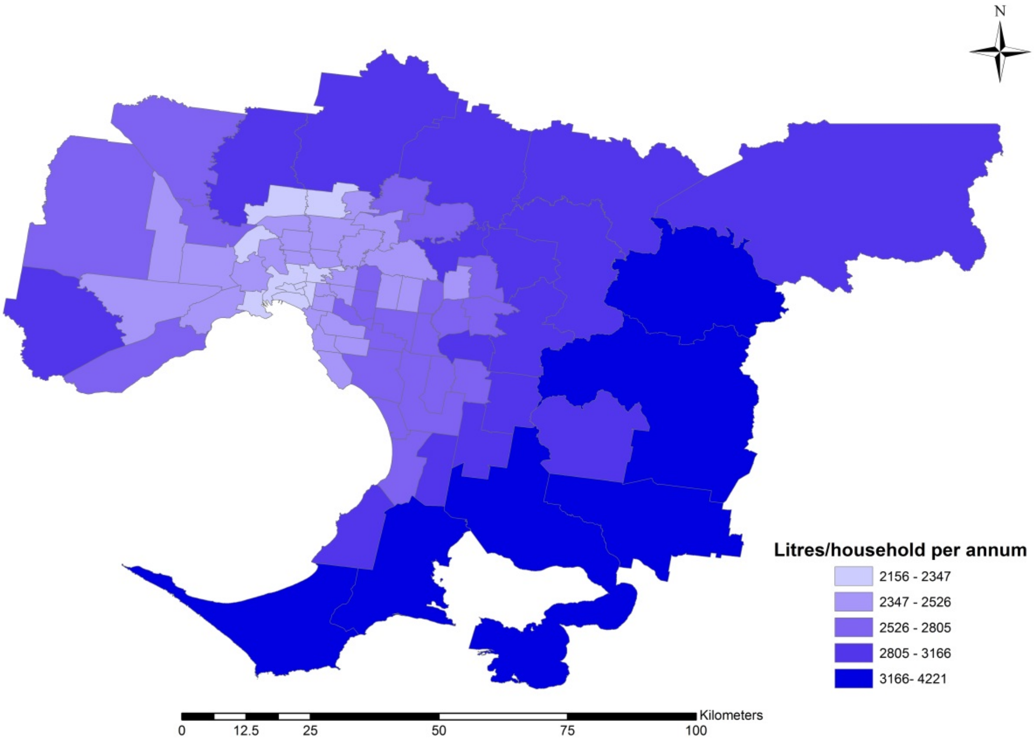


Figure 7.4. Primary fuel consumption (base-case scenario, 2030)

- ***Activity-centres scenario***

  More apartments and units compared to other dwelling types, shorter distance to public transport stations, and higher walkability in activity centres compared to the base-case scenario reduce car ownership, VKT, and proportion of trips by cars in activity centres, and consequently result in less energy and crude oil consumption. Households would consume 1.284E+11 MJ of energy per year, which is equivalent to 3.67E+09 litres of primary fuel (Figure 7.5) (see 'activity centre scenario-2030\ environmental indicators\ resource depletion-crude oil activity 2030.xlsx' in Appendix 3).

- ***Fringe-focus Scenario***

  More developments in the fringe-focus scenario compared to the base-case scenario increase car ownership, VKT, and proportion of trips by cars in the fringe and consequently results in more energy and primary oil consumption. Households would consume 1.29E+11 MJ of energy per year, which is equivalent to 3.68E+09 litres of primary fuel (Figure 7.5) (see 'fringe scenario 2030\ environmental indicators\resource depletion-crude oil fringe 2030.xlsx'in Appendix 3).Figure 7.5 provides a clear illustration of differences between 2006, and 2030 scenarios in terms of non-renewable resource depletion.

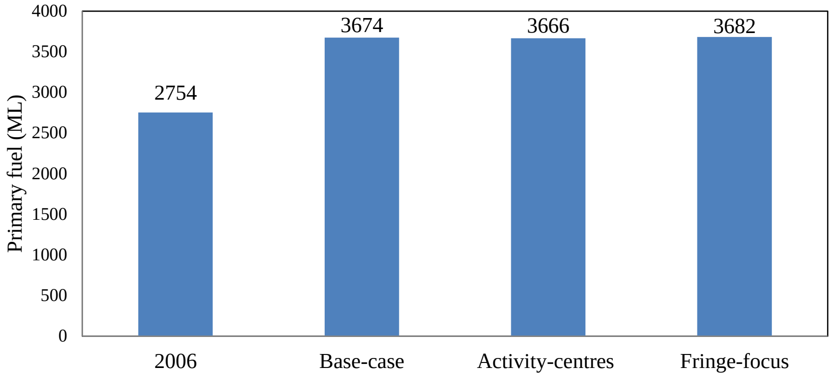


Figure 7.5. Total primary fuel consumption (ML) for different scenarios

7.3.2. GHG emissions

- ***Base-case scenario***

  Household GHG emissions would reduce 9.4% compared to 2006, while total GHG emissions for all Melbournian households would increase from 5.49E+9 kg to 7.36E+9 kg. Figure 7.6 visualises household annual GHG emissions in the base-case scenario in 2030 (see 'base case scenario-Victoria plan\ environmental indicators\energy and emission-2030.xlsx' in Appendix 3).

- ***Activity-centres scenario***

  Lower car ownership, VKT and car usage in this scenario compared to the base-case scenario results in 1.6E+7 kg reduction in GHG emissions for transport for all Melbournian households (Figure 7.7)(see 'activity centre scenario-2030\ environmental indicators\ energy and emission- activity centres2030.xlsx' in Appendix 3).

- ***Fringe-focus scenario***

  Higher car ownership, VKT and car usage in this scenario compared to the base-case scenario results in 1.7E+7 kg increase in GHG emissions for transport (Figure 7.7) (see 'fringe scenario 2030\ environmental indicators\energy and emission-fringe 2030.xlsx' in Appendix 3).

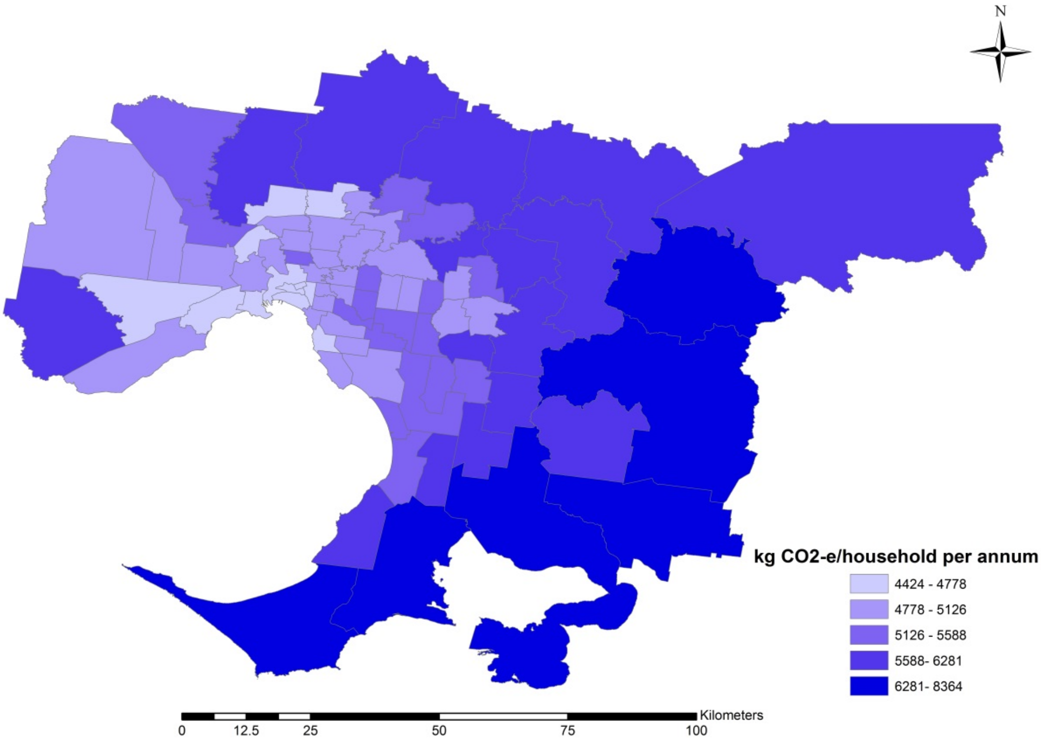


Figure 7.6. GHG emissions (base-case scenario, 2030)

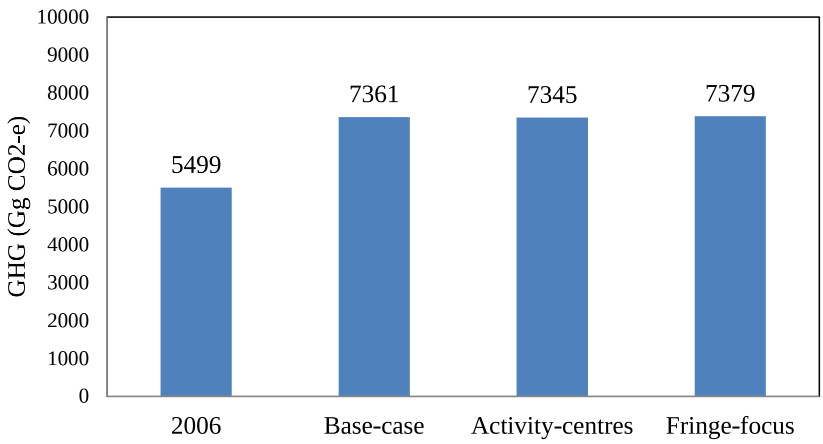


Figure 7.7. Total GHG emissions (Gg CO_2-e) for different scenarios

7.3.3. Other air pollutants

- ***Base-case scenario***

The total air pollutants of PM_{10}, NO_x, and CO would increase from 1.05E+8 kg in 2006 to 1.38E+8 kg in 2030 for all Melbournian households. However, emissions per household would reduce by 11.5% compared to 2006. Figure 7.8 illustrates annual air pollutants emissions per household in the base-case scenario (see 'base case scenario-Victoria plan\ environmental indicators\energy and emission-2030.xlsx' in Appendix 3).

- ***Activity-centres scenario***

The total air pollutants of PM_{10}, NO_x, and CO would increase from 1.386E+8 kg in the base-case scenario to 1.383E+8 kg in this scenario for all Melbournian households (Figure7.9) (see 'activity centre scenario-2030\ environmental indicators\ energy and emission- activity centres2030.xlsx' in Appendix 3).

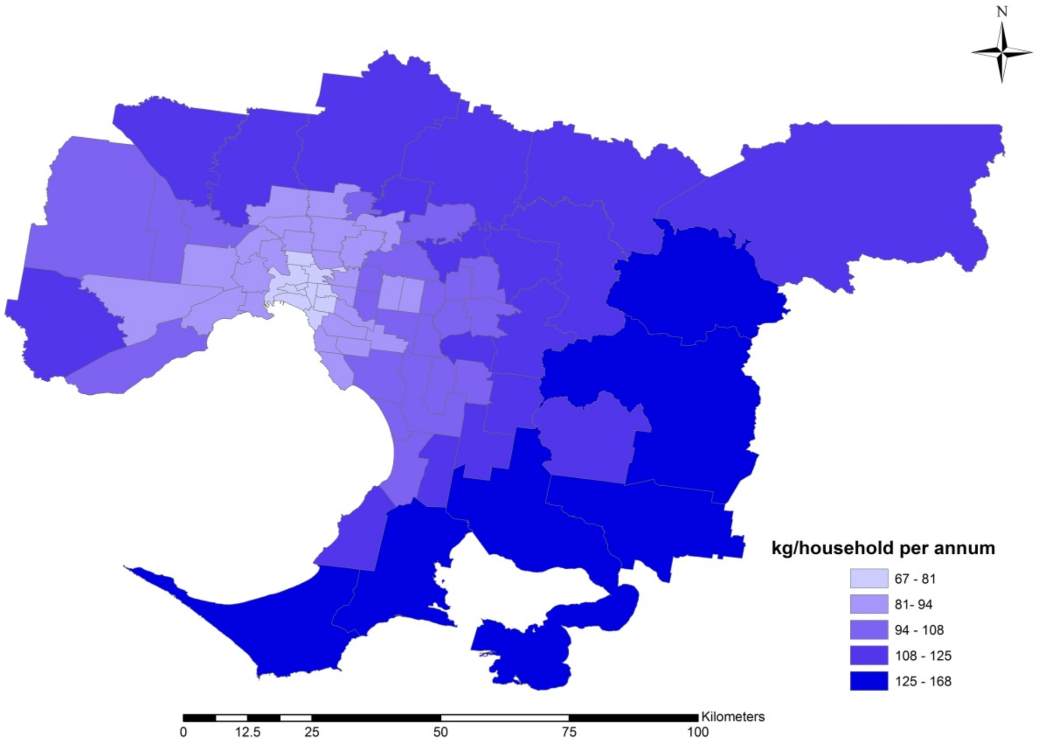


Figure 7.8. Air pollutants (PM_{10}, NO_x, and CO) emissions (base-case scenario, 2030)

- ***Fringe-focus scenario***

The total air pollutants of PM_{10}, NO_x, and CO would increase from 1.386E+8 kg in the base-case scenario to 1.388E+8 kg in this scenario (Figure 7.9) (see 'fringe scenario 2030\ environmental indicators\energy and emission-fringe 2030.xlsx' in Appendix 3).

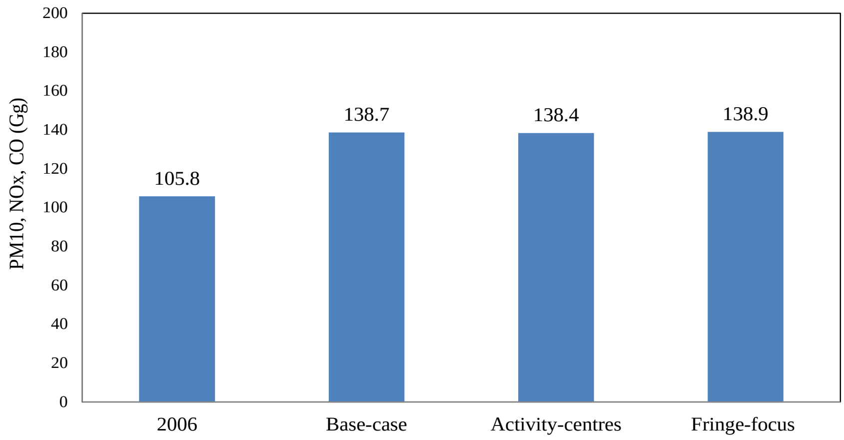


Figure 7.9. The total air pollutants of PM_{10}, NO_x, CO for different scenarios

7.3.4. Land consumption for transport

- ***Base-case scenario***

As discussed earlier in Chapter 6, it was assumed that road area per capita is constant over time. So by considering population growth in 2030, land consumption for transport would be 382 km^2, which is 2.2 times more than 2006 (Figure 7.10) (see 'base case scenario-Victoria plan\ environmental indicators\land consumption for roads 2030.xlsx'in Appendix 3).

- ***Activity-centres scenario***

With 40% less land devoted to transport in activity centres, the activity-centres scenario would have 75 km^2 less land devoted to transport compared to the base-case (Figure 7.10) (see 'activity centre scenario-2030\ environmental indicators\ land consumption for roads 2030.xlsx'in Appendix 3).

- ***Fringe-focus scenario***

With 40% more land devoted to transport in green wedges, the fringe-focus scenario would have 70 km^2 land devoted to transport compared to the base-case scenario (Figure 7.10) (see 'fringe scenario 2030\environmental indicators\land consumption for roads 2030.xlsx'inAppendix 3).

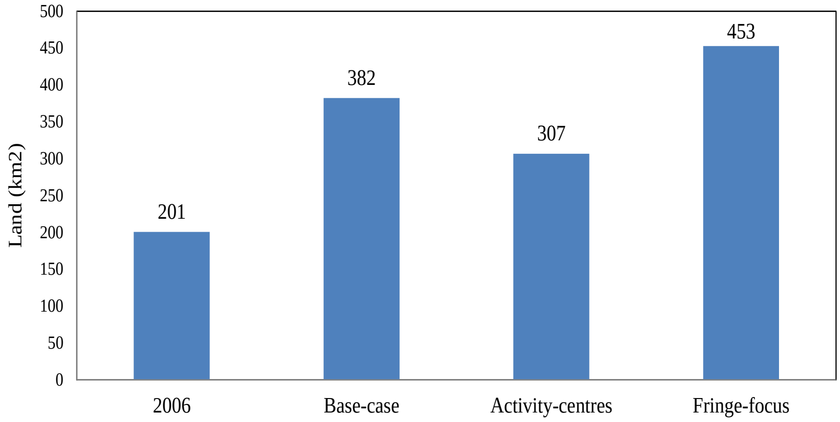


Figure 7.10. Land consumption for transport (km^2) for different scenarios

7.4. Social indicators

In this section, accessibility, fatalities and injuries related to traffic accidents, and mortality effects of air pollutants are quantified for the scenarios in 2030, which were developed for this study.

7.4.1. Accessibility

- ***Base-case scenario***

The process of accessibility quantification for 2006 and 2030 was provided in Chapter 4, and 6 in detail. Based on the results of the calculations, accessibility would increase from 0.34 in 2006 to 0.48 in 2030. Figure 7.11 illustrates accessibility for the base-case scenario in Melbourne (see 'base case scenario-Victoria plan\ social indicators\accessibility index\accessibility index 2030.xlsx' in Appendix 3).

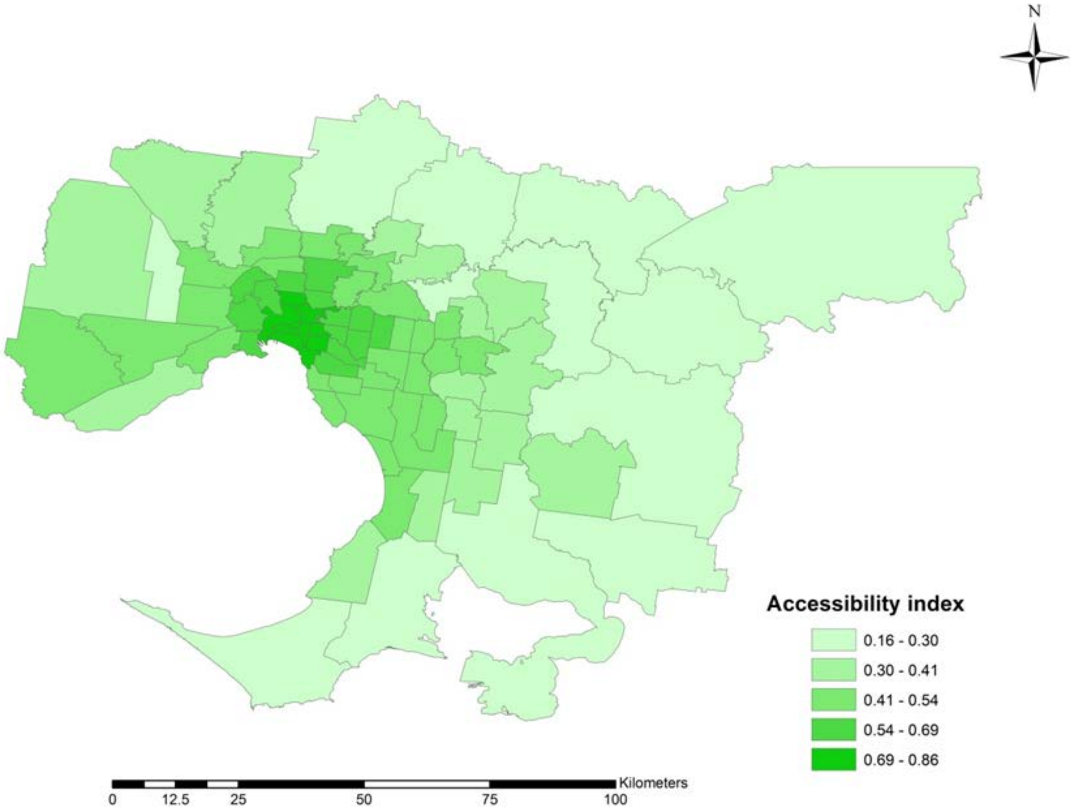


Figure 7.11. Accessibility index (base-case scenario, 2030)

- ***Activity-centres scenario***

  As a results of improvement in walkability and access to public transport in activity centres compared to the base-case scenario, overall accessibility index would increase by 29% (Figure 7.12, 7.13, 7.14) (see 'activity centre scenario-2030\ social indicators\ accessibility index 2030-activity centre.xlsx' in Appendix 3).

- ***Fringe-focus scenario***

  Accessibility index would reduce from 0.48 in the base-case scenario to 0.33 in this scenario (Figure 7.12, 7.13, 7.14) (see 'fringe scenario 2030\social indicators\accessibility index 2030.xlsx'in Appendix 3).

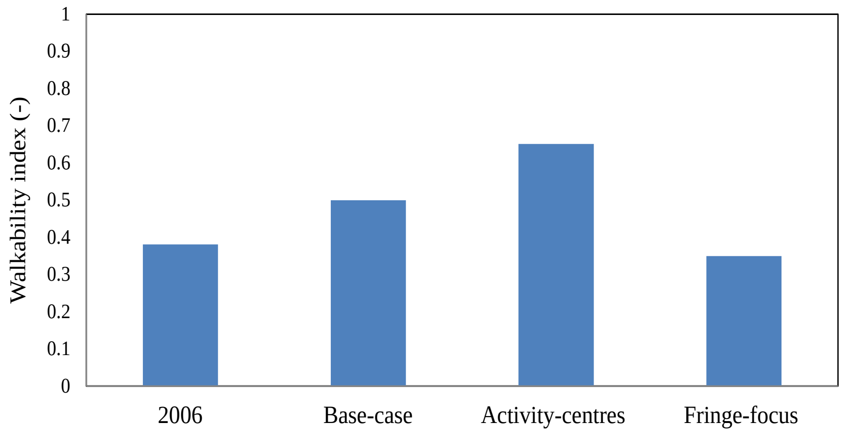


Figure 7.12. Walkability index for different scenarios

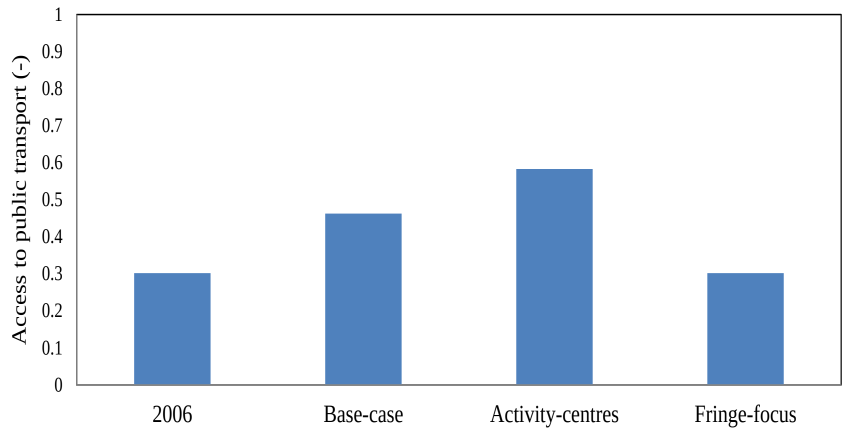


Figure 7.13. Access to public transport for different scenarios

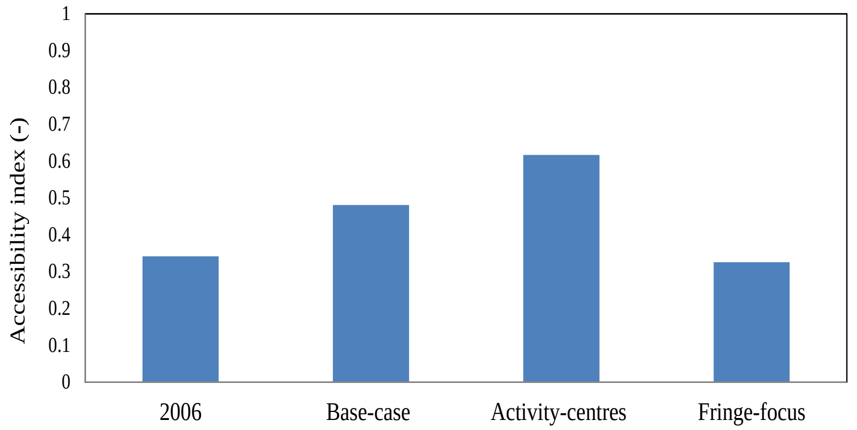


Figure 7.14. Overall accessibility index for different scenarios

7.4.2. Fatalities and injuries related to traffic accidents

- ***Base-case scenario***

  Annual fatalities due to accidents for all households would decrease from 162 in 2006 to 74.5 in 2030, while injuries related to accidents would increase from 2998 in 2006 to 4213 in 2030. Figures 7.15 and 7.16 illustrate fatalities and injuries related to accidents respectively (see 'base case scenario-Victoria plan\ social indicators\death due to accident.xlsx' in Appendix 3).

- ***Activity-centres scenario***

  Due to lower VKT in this scenario compared to the base-case one, accident fatalities and injuries would reduce from 4287 persons in the base case scenario to 4279 persons in this scenario (Figure 7.17, 7.18) (see 'activity centre scenario 2030\social indicators\death due to accident-activity centre.xlsx' in Appendix 3).

- ***Fringe-focus scenario***

  Due to higher VKT in this scenario, accidents fatalities and injuries would increase from 4287persons in the base-case scenario to 4296 persons in this scenario (Figure 7.17, 7.18) (see 'fringe scenario-2030\ social indicators\ death due to accident-fringe.xlsx' in Appendix 3).

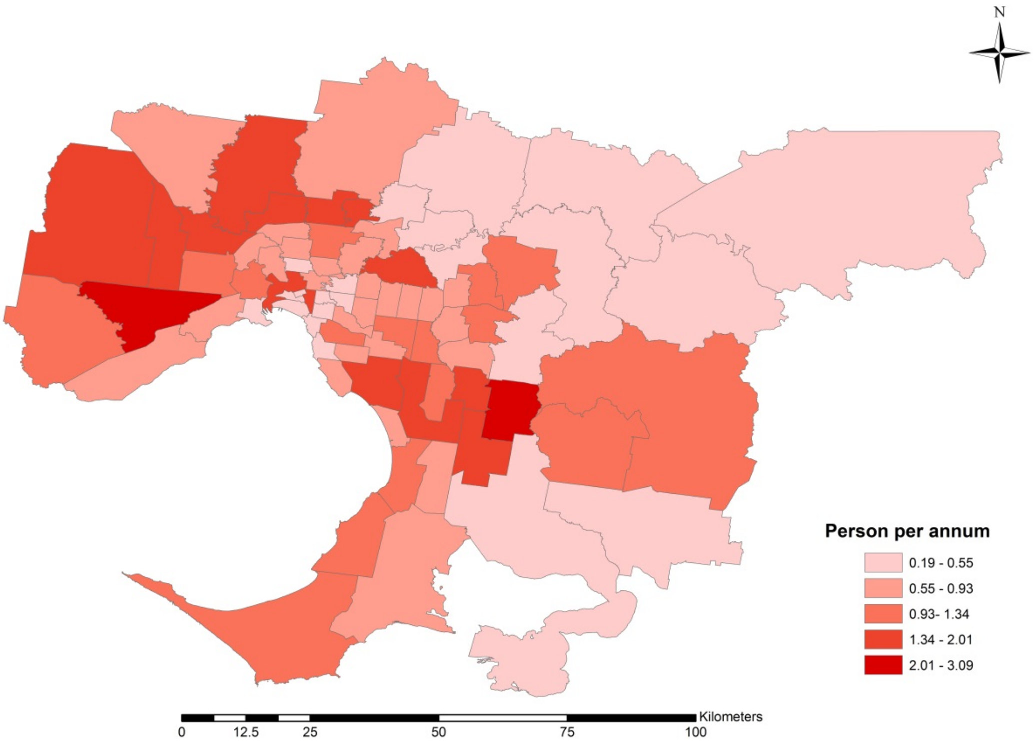


Figure 7.15. Accident fatalities related to transport (base-case scenario, 2030)

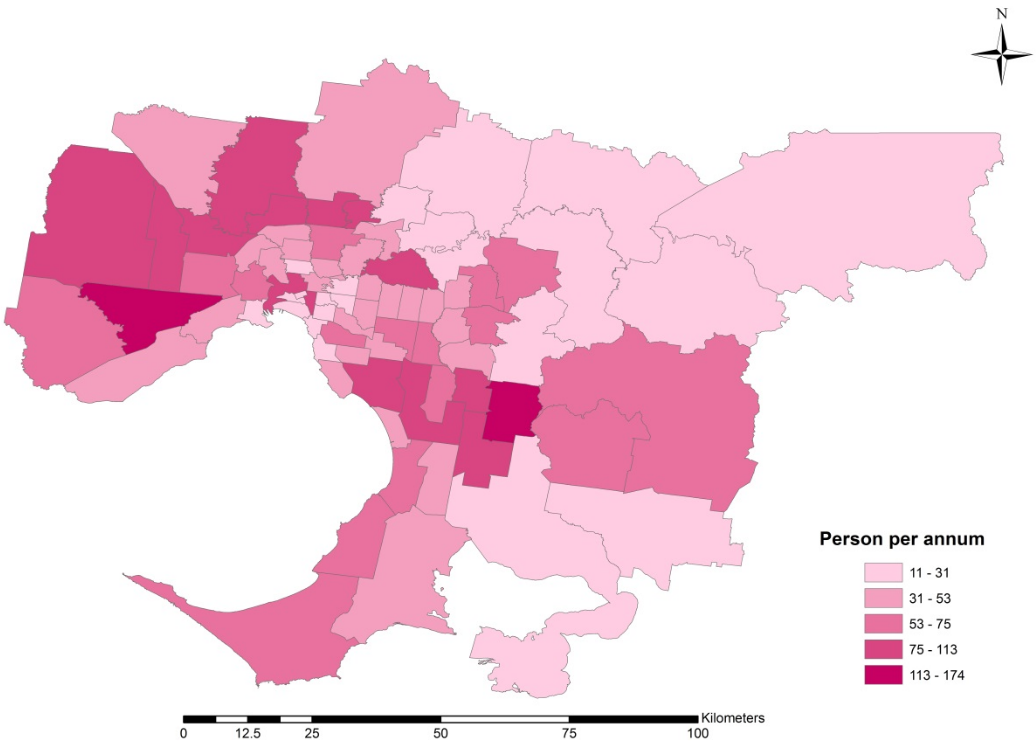


Figure 7.16. Accident injuries related to transport (base-case scenario, 2030)

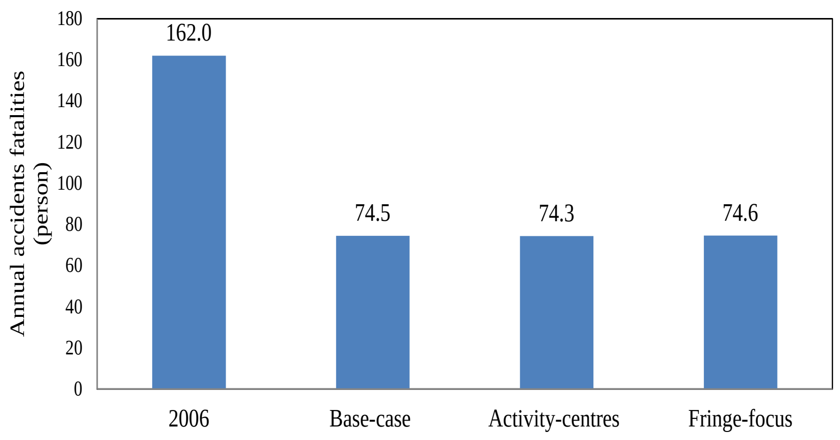


Figure 7.17. Annual fatalities related to accidents for different scenarios

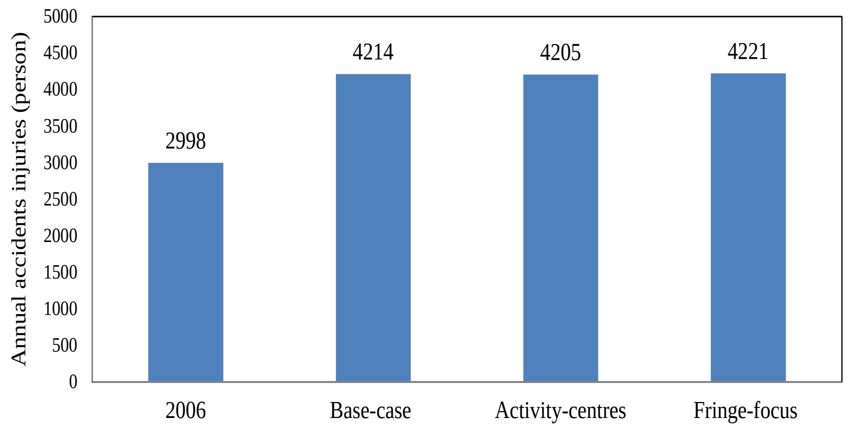


Figure 7.18. Annual injuries related to accidents for different scenarios

7.4.3. Mortality effects of air pollutants

- ***Base-case scenario***

  Annual deaths due to air pollutants would increase from 72 in 2006 to 169 in 2030. As number of population and number of deaths are effective factors in calculating mortality related to air pollutants (Chapter 3), increases in population and deaths in 2030 compared to 2006(Chapter 6), cause increase in deaths related to air pollutants. Figure 7.19 represents deaths due to air pollutants in each SLA in the base-case scenario in 2030 (see 'base case scenario-Victoria plan\ social indicators\death due to PM_{10}.xlsx' in Appendix 3).

- ***Activity-centres scenario***

  Due to lower emissions in this scenario compared to the base-case scenario, annual death due to air pollutants would reduce by 0.2% compared to the base-case scenario (Figure 7.20) (see 'activity centre scenario-2030\ social indicators\ death due to emission.xlsx' in Appendix 3).

- ***Fringe-focus scenario***

  Due to higher emissions in this scenario compared to the base-case scenario, mortality effects of air pollutants would increase by 0.2% compared to the base-case scenario (Figure 7.20) (see 'fringe scenario 2030\social indicators\death due emission.xlsx' in Appendix 3).

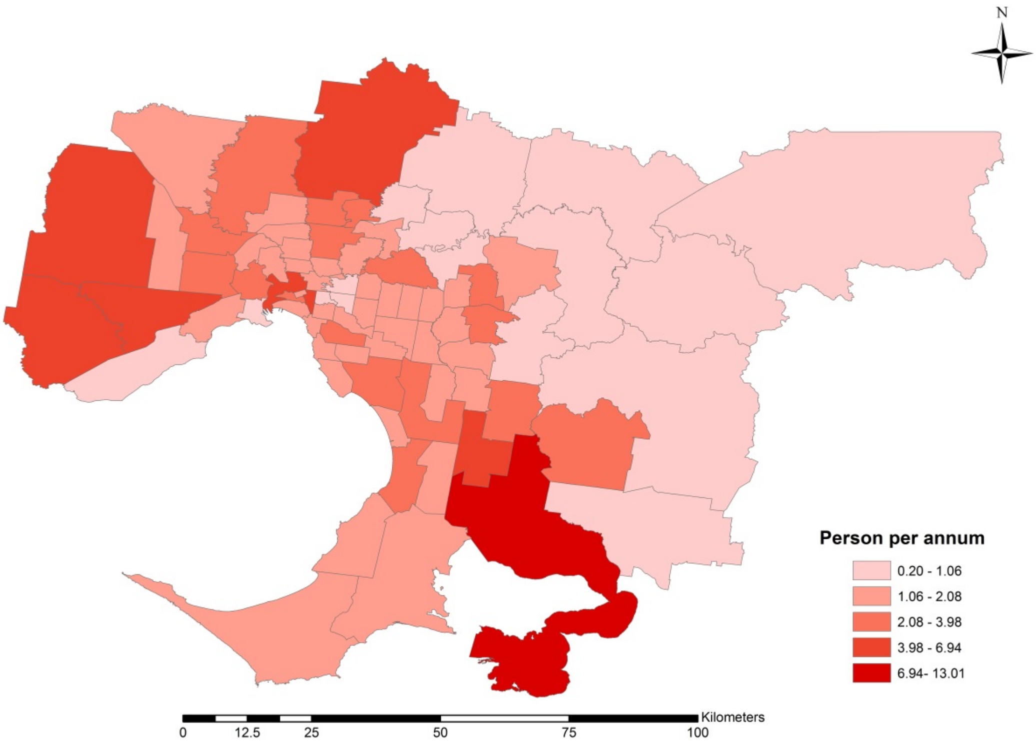


Figure 7.19. Annual number of death due to air pollutants (base-case scenario, 2030)

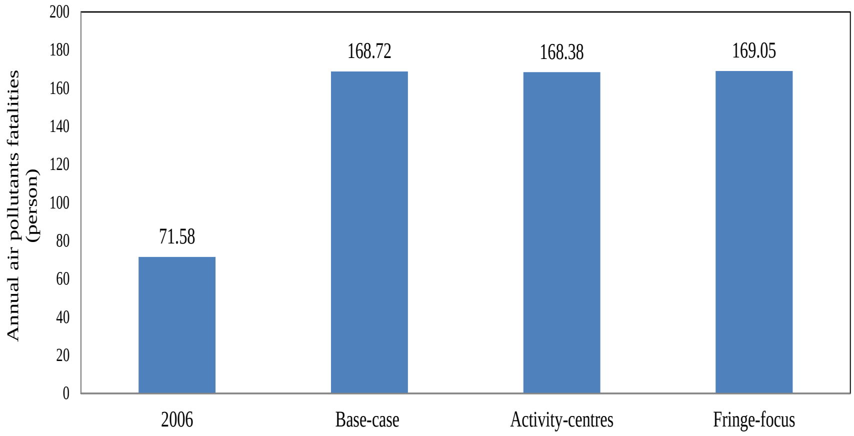


Figure 7.20. Annual fatalities related to air pollutants for different scenarios

7.5. Economic indicators

Selected economic indicators (car-ownership costs and operation costs of public transport, vehicle and general costs of accidents, benefits of active transport) were quantified for the developed scenarios in 2030, using inputs presented in Chapter 6.

7.5.1. Car-ownership costs and public transport operation costs

- **Base-case scenario**

Due to 0.01 annual reductions in costs, according to RACV (2011) , annual costs of car ownership and public transport operation per household would be $11,445 compared to$16,201 in 2006 (Figure 7.21). However due to larger number of households in 2030, total costs for all households would be $1.57E+10 compared to $1.50E+10 in 2006 (Figure 7.22) (see ‘base case scenario-Victoria plan\ economic indicators\car ownership cost.xlsx’ in Appendix 3).

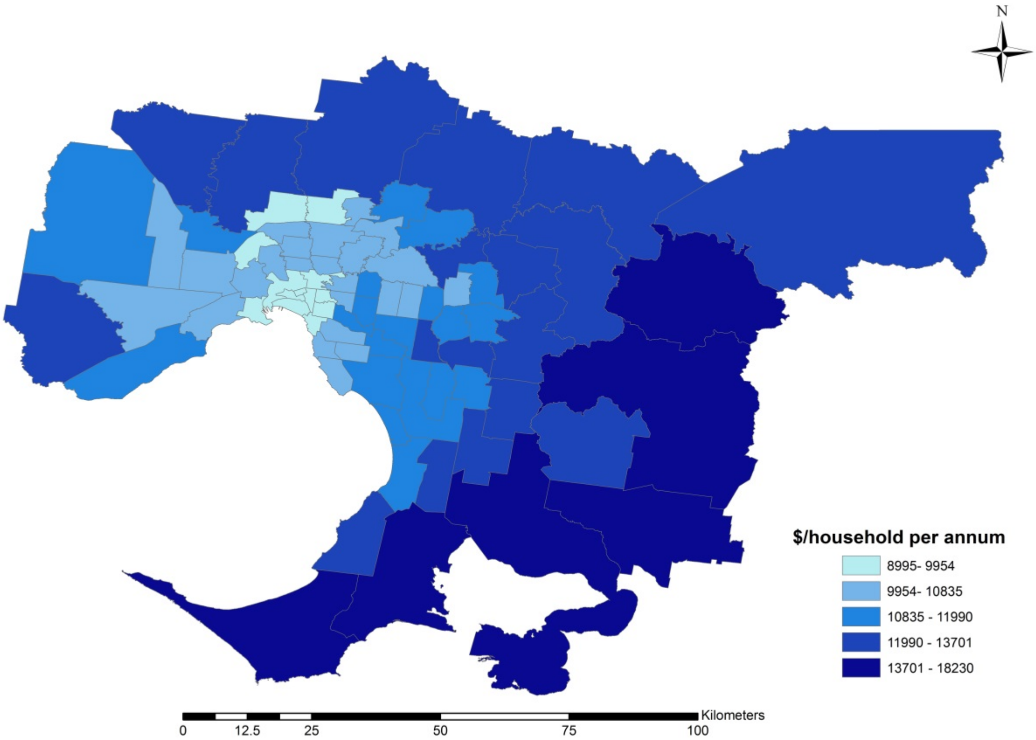


Figure 7.21. Annual costs of car ownership and public transport operation (base-case scenario, 2030)

- ***Activity-centres scenario***

  Due to less VKT in the activity-centres scenario compared to the base-case scenario, annual costs associated with transport operation would decrease from $1.57E+10 to $1.56E+10 (Figure 7.22) (see 'activity centre scenario-2030\ economic indicators\ car ownership cost.xlsx' in Appendix 3).

- ***Fringe-focus scenario***

  Due to higher VKT in the fringe scenario compared to the base-case scenario, costs associated with transport operation would increase from $1.570E+10 to $1.574E+10 (Figure 7.22) (see 'fringe scenario 2030\economic indicators\car ownership cost.xlsx' in Appendix 3).

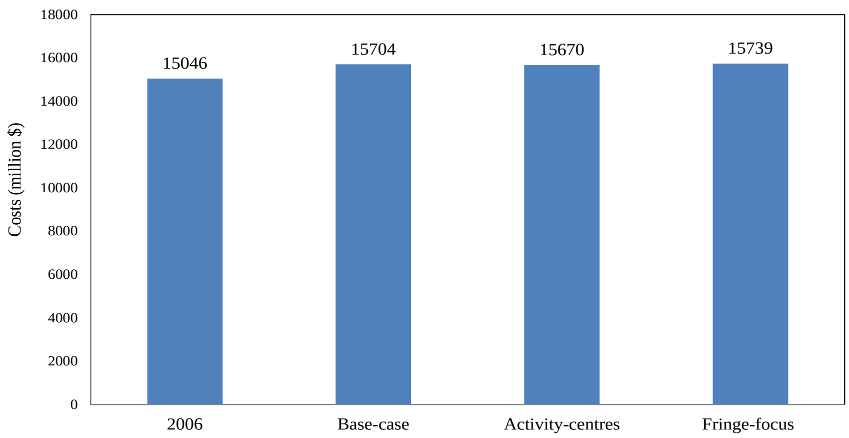


Figure 7.22. Annual car ownership and public transport operation costs (Million dollars) for different scenarios

7.5.2. Vehicle and general costs of accidents

- ***Base-case scenario***

  Due to lower number of fatalities related to accidents (Section 7.4.2) and lower ratio of vehicle and general costs to human costs (Chapter 6) in 2030 compared to 2006, vehicle and general costs of accidents would decrease from $660,993,719 in 2006 to $427,754,404 in 2030 (Figure 7.23, 7.24) (see 'base case scenario-Victoria plan\ economic indicators\crash fatality and injury costs.xlsx' in Appendix 3).

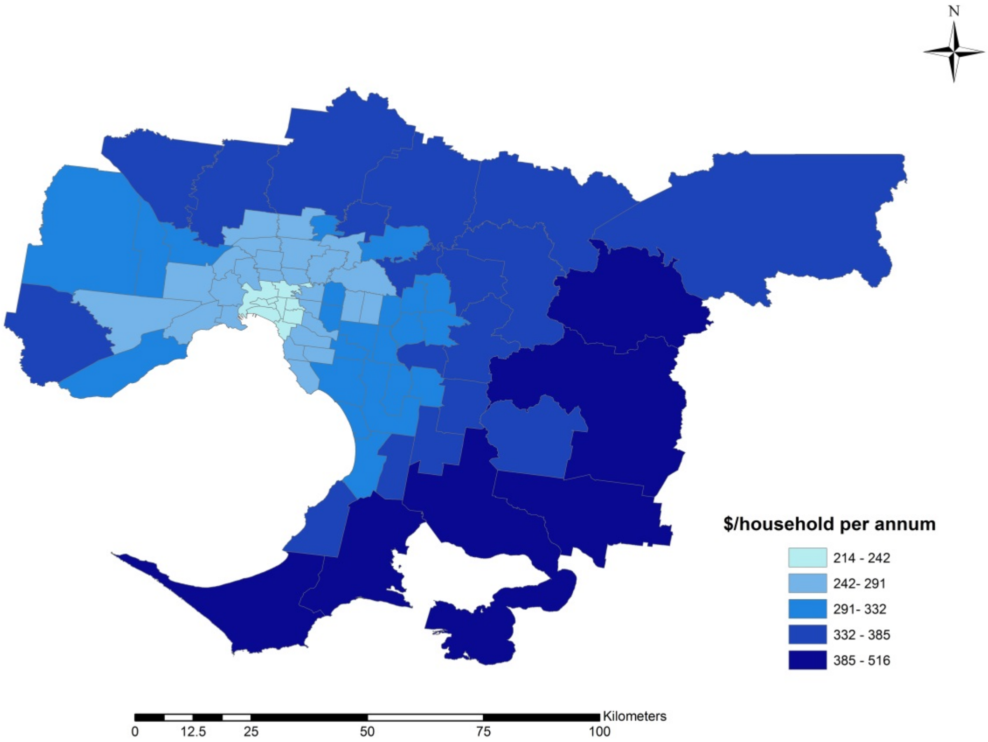


Figure 7.23. Annual vehicle and general costs of accidents (base-case scenario, 2030)

- ***Activity-centres scenario***

  Lower number of accidents reduces costs of accidents in activity-centres scenario from $427,754,404 to $426,863,215 compared to the base-case scenario (Figure 7.24) (see 'activity centre scenario-2030\ economic indicators\ crash fatality and injury costs.xlsx' in Appendix 3).

- ***Fringe-focus scenario***

  Higher number of accidents increases costs of accidents in fringe-focus scenario from $427,754,404 to $428,520,013 compared to the base-case scenario (Figure 7.24) (see 'fringe scenario 2030\economic indicators\crash fatality and injury costs.xlsx' in Appendix 3).

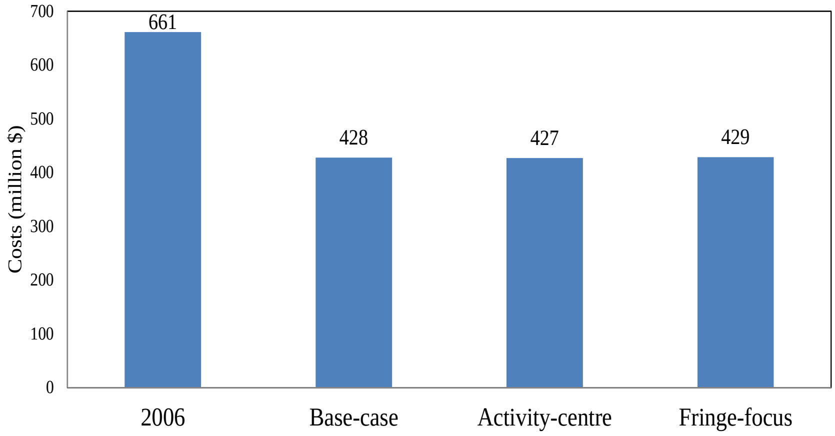


Figure 7.24. Annual vehicle and general costs of accidents (million dollars) for different scenarios

7.5.3. Benefits of walking and cycling

- ***Base-case scenario***

  Due to higher walkability in 2030 compared to 2006 (Chapter 6), benefits of walking and cycling would increase from $564 per household to $857 (Figure 7.25). Active transport benefits per household are shown in Figure 7.26 (see 'base case scenario-Victoria plan\ economic indicators\benefit of walking and cycling\ total benefits-base.xlsx' in Appendix 3).

- ***Activity-centres scenario***

  Higher walkability and lower percentage of car usage in the activity-centres scenario would increase walking and cycling benefits for all households from $1,120,883,932 to $4,034,713,130 compared to the base-case (Figure 7.26) (see 'activity centre scenario-2030\ economic indicators\benefit of walking and cycling\total benefit of walking.xlsx' in Appendix 3).

- ***Fringe-focus scenario***

  Lower walkability and higher percentage of car usage in the fringe-focus scenario reduces walking and cycling benefits for all households from 1,120,883,932 to $1,107,446,235 compared to the base-case one (Figure 7.26) (see 'fringe scenario 2030\economic indicators\benefit of walking and cycling\ total benefit of walking.xlsx' in Appendix 3).

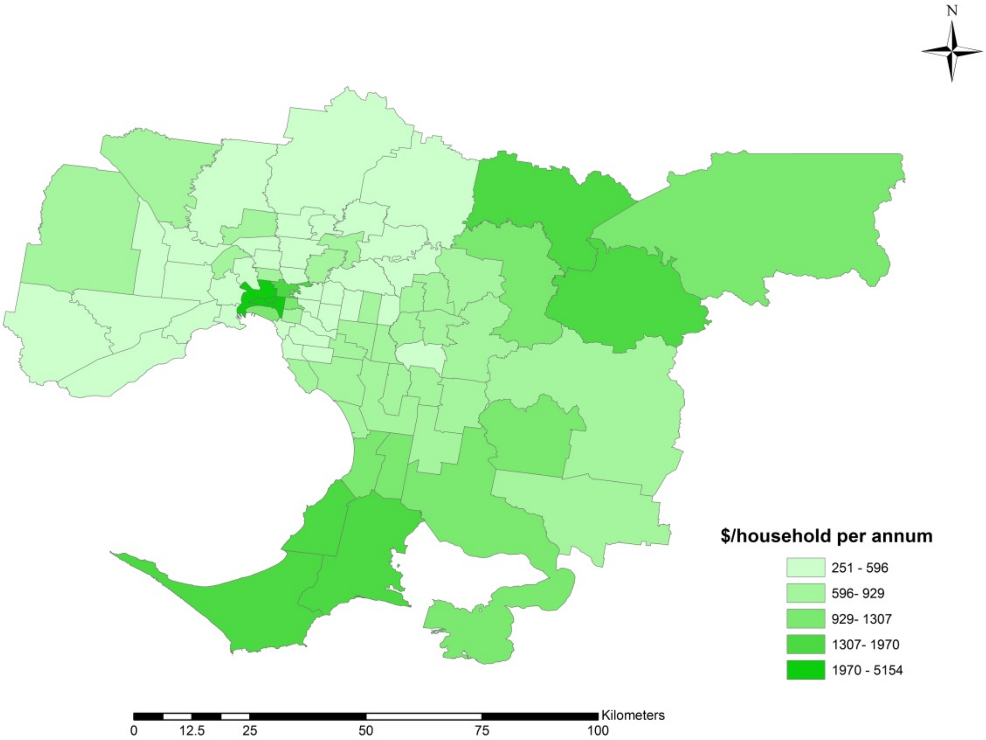


Figure 7.25. Annual benefits of walking and cycling (base-case scenario, 2030)

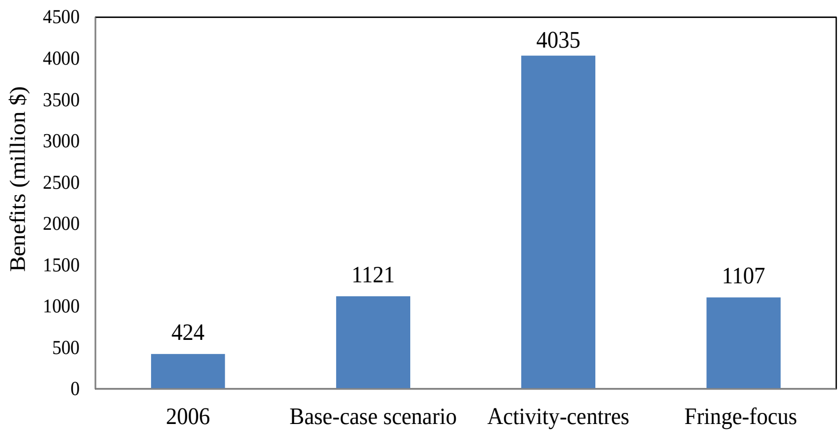


Figure 7.26. Annual benefits of walking and cycling (million dollars) for different scenarios

7.6. Transport sustainability index

The process of normalisation, weighting and aggregation (Chapter 5) was repeated for selected indicators for all developed scenarios.

➢ ***Base-case scenario***

Sustainable transport in the base-case scenario can be considered on two levels. On a household level, the results showed that Melbourne would have more of a sustainable future in 2030 compared to 2006. Transportation sustainability per household would improve from 0.61 to 0.66. Transportation environmental impact index (TEII), transportation social impact index (TSII), and transportation economic impact index (TCII) also would improve compared to 2006 at a household level (Figure 7.27) (see 'base case scenario-Victoria plan\ final index-PCA-household level\final index.xlsx' in Appendix 3).

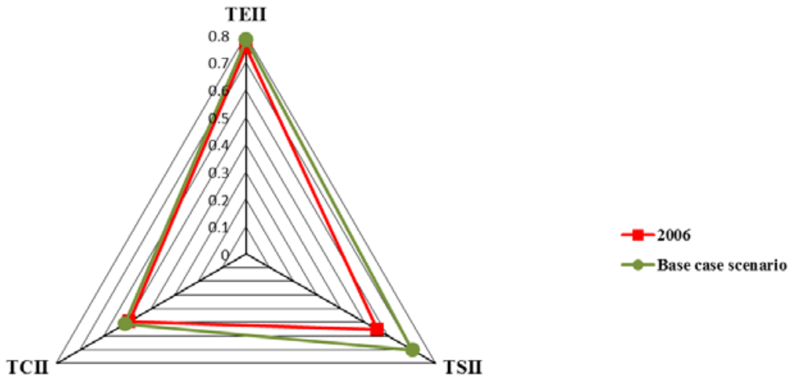


Figure 7.27.Transport sustianaility indices in household level (2006, 2030)

On a larger level, transport sustainability for all households would decrease from 0.66 in 2006 to 0.65 in 2030. This reduction is because of the increase in household numbers compared to 2006. Even on an economic level, despite population increase, the transport economic sustainability index would improve from 0.48 in 2006 to 0.51 in 2030 (Figure 7.28) (see 'base case scenario-Victoria plan\ final index-PCA-all households\final economic index.xlsx' in Appendix 3). Comparisons between the transport sustainability index in 2006 and 2030 showed that population increase would have a small impact on sustainability index reduction in the future. So, urban planning in 2030, which advocates for more sustainable development, would lead to more sustainable transport. Figure 7.29 illustrates transport sustainability index for all Melbourne's SLA in 2030.

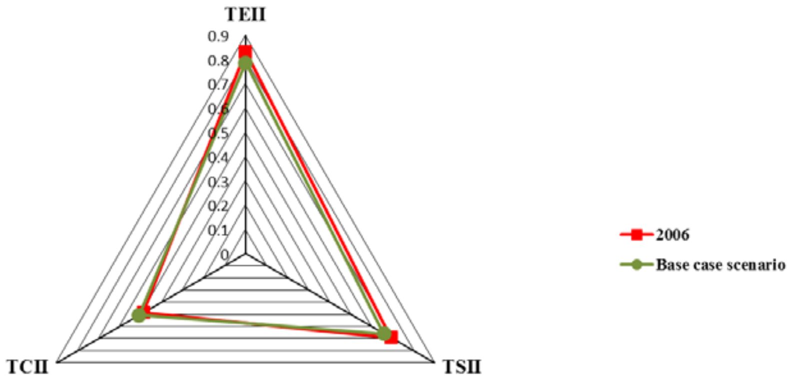


Figure 7.28.Transport sustainability indices for all households (2006, 2030)

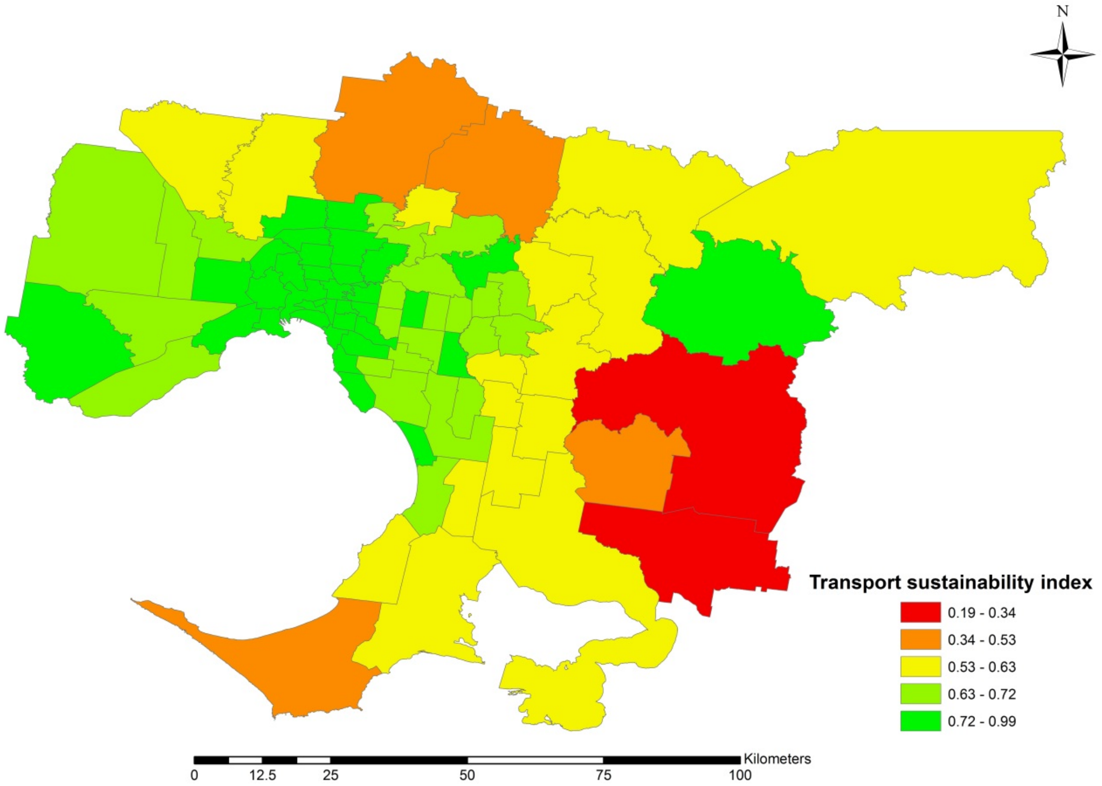
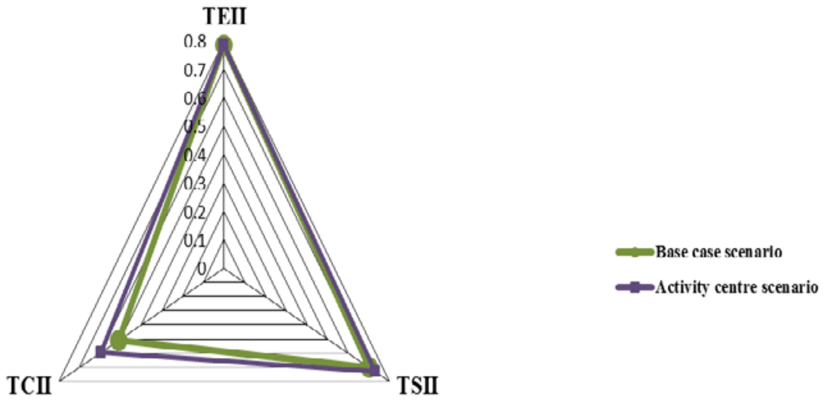


Figure 7.29. Household transport sustainability index (2030)

➢ ***Activity-centres scenario***

The results showed that transport sustainability would increase in all dimensions in the activity-centres scenario compared to the base-case scenario (Figure 7.30). Overall transport sustainability would increase in this scenario by 5.7% compared to the base-case. This increase is probably due to the improvement in transport facilities in activity centres, which are the centres where more population and employment growth is expected in the future. Figure 7.31 illustrates transport sustainability index in all Melbourne SLAs for the activity-centres scenario (see 'activity centre scenario-2030\ final index-PCA-household level\final index.xlsx' in Appendix 3).



➢ ***Fringe-focus scenario***

The results show that the transport sustainability slightly decreases in all dimensions in the fringe-focus scenario compared to the base-case scenario (Figure 7.32). Overall sustainability would decrease in this scenario by 1.5% compared to the base-case. This reduction is probably due to the dispersion in city development, which causes more travel. Figure 7.33 illustrates the transport sustainability index in all Melbourne SLAs for this scenario (see 'fringe scenario 2030 final index-PCA-household level\final index.xlsx' in Appendix 3).

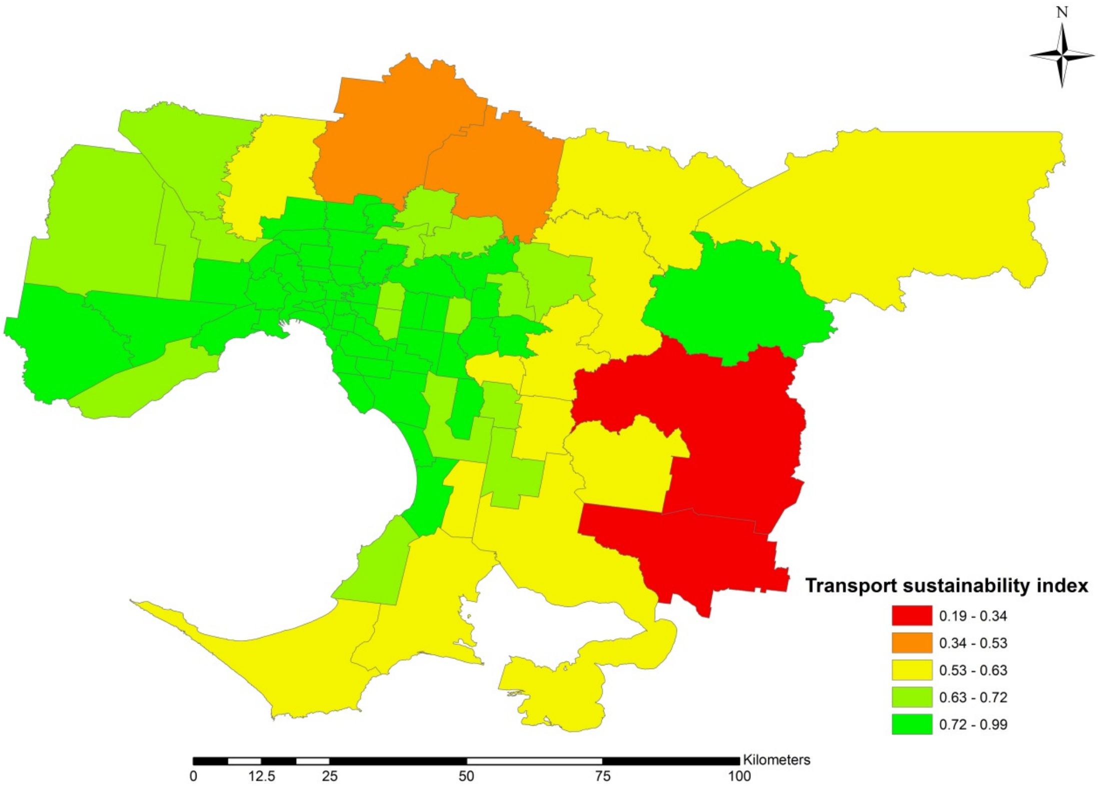


Figure 7.31. Transport sustainability index (activity-centres scenario, 2030)

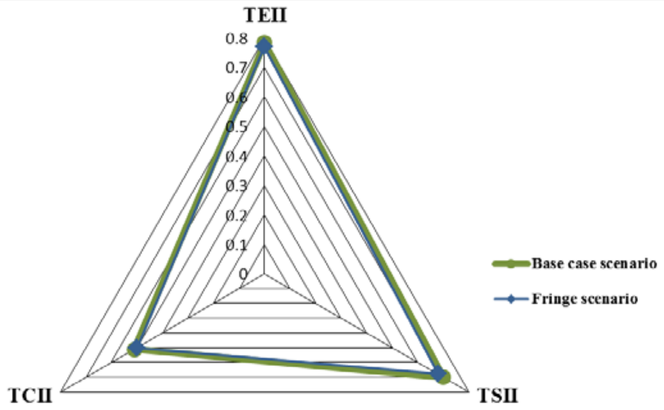


Figure 7.32. Transport sustainability index (base-case and fringe-focus scenarios, 2030)

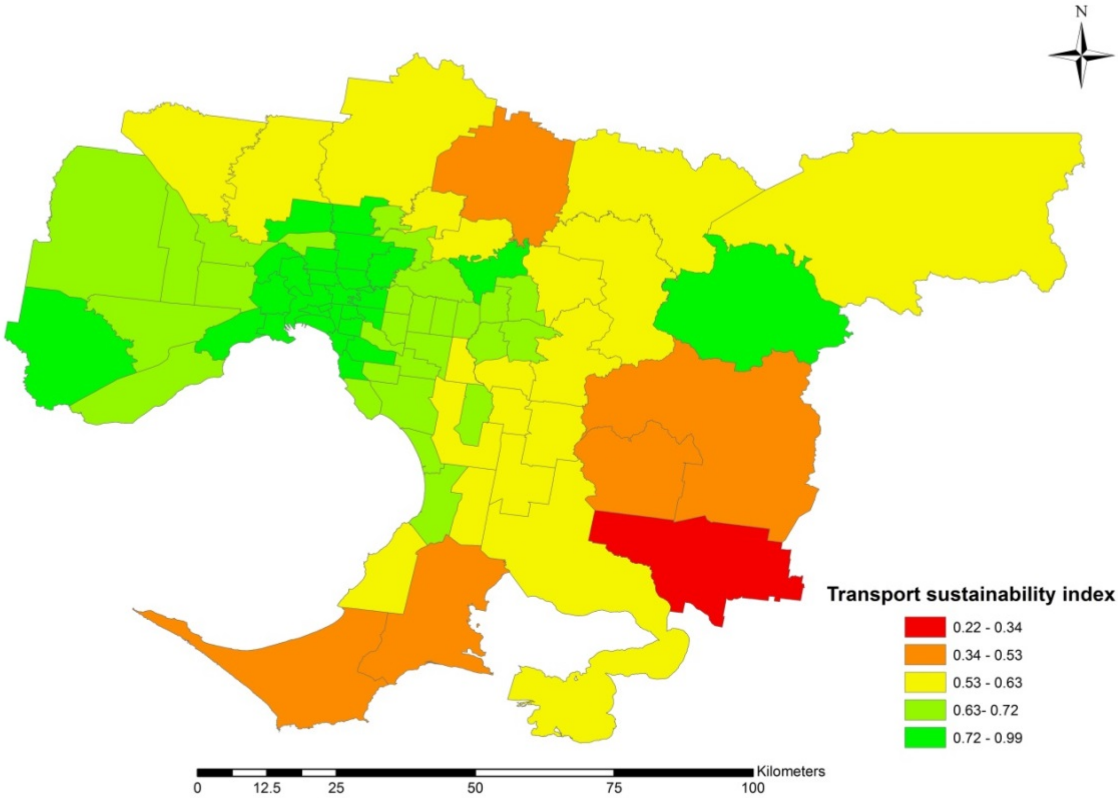


Figure 7.33. Transport sustainability index (fringe-focus scenario, 2030)

7.7. Chapter summary

Transport sustainability indices were developed for three urban-planning scenarios in this chapter. The base-case scenario, which is based on the government plan for urban development, would cause an 8% increase in transport sustainability index in 2030 compared to 2006. Regardless of the population increase, the government would achieve its aim in providing a more sustainable city. This improvement in transport sustainability can be achieved by concentrating major developments in activity centres, and shifting away from growth in the city fringe. To contrast different urban-planning strategies, two opposing focuses were compared with the base-case. As expected, more developments in the fringe would increase travel and cause lower sustainability indices compared to more developments in activity centres. So the results of this chapter confirm the compact city theory, which was discussed earlier in Chapter 2. To summarise the results, indicators and indices for all investigated scenarios are presented in Tables 7.1, 7.2, 7.3, 7.4.

Table 7.1. Environmental indicators at household level for all SLAs

	Depletion of non-renewable resources (L)	GHG emission (kg)	Other emissions (kg)	Land consumption for transport (km^2)
2006	237,561	474,425	9,122	0.020
Base-case scenario	214,330	429,638	8,070	0.030
Activity-centres scenario	213,887	428,745	8,054	0.026
Fringe-focus scenario	214,773	430,607	8,079	0.038

Table 7.2. Social indicators at household level for all SLAs

	Accessibility	Fatalities and injuries related to accidents	Mortality effects of air pollutants
2006	0.34	0.2723	0.00578
Base-case scenario	0.48	0.2496	0.01070
Activity-centres scenario	0.61	0.2491	0.01068
Fringe -focus scenario	0.32	0.2499	0.01073

Table 7.3. Economic indicators at household level for all SLAs

	Car ownership and public transport operation costs ($)	Vehicle and general costs of accidents ($)	Benefits of walking and cycling ($)
2006	1,312,289	56,972	45,157
Base-case scenario	915,635	24,905	68,587
Activity centres scenario	913,759	24,856	213,224
Fringe-focus scenario	917,444	24,936	66,928

Table 7.4. Transport sustainability indices

	TEII	TSII	TCII	I_{CST}
2006	0.75	0.55	0.49	0.61
Base-case scenario	0.78	0.70	0.51	0.66
Activity-centres scenario	0.79	0.73	0.59	0.70
Fringe-focus scenario	0.77	0.68	0.50	0.65

Chapter 8

Discussion and Conclusions

8.1. Introduction

This research aims to develop transport related environmental, social and economic indices for urban-development scenarios. These indices are intended to be used to assess selected urban-planning strategies and their effects on transport sustainability. To achieve the aim, five objectives were defined:

1. Identify and select relevant transport indicators (environmental, social and economic).
2. Develop an integrated model for greenhouse gas (GHG) emissions estimation, and quantify other environmental indicators based on the integrated model.
3. Quantify social and economic indicators using the results of the integrated model as preliminary inputs.
4. Normalise indicators and verify their weights to derive indices.
5. Predict transportation environmental impact index (TEII), transportation social impact index (TSII), transportation economic impact index (TCII) for different urban development scenarios for Melbourne Statistical Local Areas (SLAs) in 2030.

To achieve the thesis aim and objectives, three different modelling techniques (linear regression model, log-linear regression model, artificial neural network model) were tested to model land-use/transport interaction. After selecting the most appropriate model for estimating car ownership, vehicle kilometres travelled (VKT), and modal split as functions of land-use and socio-economic factors, these travel behaviour measurements were used to quantify selected environmental, social, and economic indicators. These indicators were selected by using a set of selection criteria discussed in Chapter 3. After quantification, suitable approaches were used to normalise, weight and aggregate indicators into transportation environmental impact index, transportation social impact index, transportation economic impact index and finally sustainable transport index. Three different urban-planning scenarios (base-case scenario, activity-centres scenario, and fringe-focus scenario) in 2030, were compared by using the indices developed. In this concluding chapter, first the approaches for answering research questions are presented. Then, before identifying areas for future research, the thesis outcomes are presented and discussed.

8.2. Research questions

Research questions and methods of approaching them are discussed in this section.

- ***Specific Question 1: How does land-use policy influence household travel behaviour (and resulting energy use)?***

Chapter 3 presented different modelling techniques (linear regression, log-linear model, artificial neural network model) to quantify car ownership, VKT, and modal split as functions of land-use and socio-economic factors. Effects of land-use factors (population density, distance from the CBD, dwelling type, distance to nearest public transport, walkability, size of SLA area) on travel behaviour were discussed for different modelling techniques. Moreover Table 3.20 provided discussion about the effects of land-use factors on travel behaviour, independent from socio-economic factors. The results showed that land-use factors are direct causes of travel behaviour.

After quantifying travel behavior measurements, energy consumptions and emissions were quantified as functions of VKT, PKT, energy and emissions factors for public and private transport.

- ***Specific Question 2: How does land-use policy influence social and economic aspects of travel?***

Quantification of car ownership, VKT and modal split helped in predicting transport energy consumption and emissions. Selected social and economic indicators were directly related to emissions and VKT level. So, using VKT and emission level in each SLA, fatalities and injuries related to accidents, mortality effects of air pollutants, car ownership costs and costs of public transport operations, vehicle and general costs of accidents, and benefits of walking and cycling were quantified in Chapter 4. It can be concluded that land-use factors affect the social and economic dimension of transport through car ownership, VKT and modal split.

- ***Specific Question 3: How does land-use policy affect transport environmental, social and economic indices?***

Chapter 6 and 7 developed a transport sustainability index for different urban-planning strategies for Melbourne in 2030. The results suggested that concentrating development in activity centres is effective in reducing the negative effects of transport and consequently increasing its sustainability. Moreover, comparing transport sustainability between 2006 and 2030, the base-case scenario at a household level showed that Melbourne will move toward better urban planning in terms of transport sustainability in 2030. However, considering all households, the transport sustainability index will reduce in 2030 compared to 2006. So, it can be concluded that lower sustainability in the future is because of population increase rather than land-use planning strategies.

By answering these questions, this thesis achieves six major outcomes, which are presented as follows.

8.3. Major outcomes

The major outcomes of this thesis are discussed in details in this section:

- ***A land-use/transport integrated model for travel behaviour analysis***

To check the ability of different techniques to model the effects of land-use and socio-economic factors on travel behaviour, three modelling techniques were compared. The selected model for this thesis (artificial neural network model) provided the lowest error, compared to linear regression and log-linear regression models. The model developed in this study was in an intermediate position between very complex land-use/transport models such as ITLUP, MEPLAN, MUSSA, UrbanSim (Hunt et al. 2005) and simple statistical models, which usually use multi-regression analysis. Moreover, this study proposed an integrated land-use/transport model, which considered land-use effects on car ownership, VKT and modal split, compared to previous studies that limited to consider land-use/VKT models or land-use/car ownership models or land use/modal split models rather than an integrated model (Corpuz et al. 2006; Whelan et al. 2010).

Although a large number of models have been developed previously to consider land-use effects on transport, they seem unsuitable because most of these models are complex models, which require large sets of data as inputs. For example, most of computational models need information about population, land-use restrictions, employment location policies, location of retail facilities, costs of travel, mode specific travel speeds and network structure, the timing of transport investment, and the general economic climate (Southworth 1995). These data sets may not be available for all locations with reasonable costs. This study developed an efficient model with a high predictability that required a minimum amount of information, which is normally available in all locations to the public. Moreover, the proposed model is very simple, and does not require complex mathematics. It can be used for all spatial scales with differing numbers of factors and for all cities easily, just by substituting factor values.

- ***Analysis of land-use/transport relationship in larger spatial scale***

Most of the available studies developed land-use/transport interaction models on household bases, while did not try to investigate if such a relationship exists for larger spatial scales. This study attempted to use Statistical Local Area (SLA) and Census Collection District (CCD) to explore if land-use/transport relationship exists in large spatial scales. The results confirmed that appropriate technique for modelling land-use/transport relationship is site specific, and type of relationship (i.e. linear and non-linear) between land-use factors and travel behaviour measurements is changed based on selected spatial scale. For example, while log-linear regression provides better results (lower NRMSE and higher R^2) for modal split in SLA, linear regression is better for predicting VKT in CCD level compared to SLA level. On the other hand, it was found that SLA level (larger spatial level) is better for land-use/transport interaction modelling, using ANN (Appendix 2).

- ***An accessibility index, as a social indicator, for Melbourne***

There are some issues with accessibility indices previously developed for Melbourne. Firstly, in some accessibility indices found in the literature (DPIE et al. 1997; Faulkner et al. 1983), straight-line distance between origins and destinations were measured, which does not capture all dimensions of accessibility. Secondly in some others (GISCA 2011), public transport were considered solely as a service to be accessed, and not as a means of potential access.

To overcome the limitations of previous reported accessibility indices, this study developed an accessibility index considering accessibility by both walking and public transport to different ranges of facilities. CCD centres were considered as points of origins to have more precise information about accessibility in different parts of each SLA. Moreover, it quantified levels of accessibility by measuring the road distances people travelled from their home to reach health facilities, education services, public transport, businesses, and parks.

- ***Specific analysis of environmental, social, economic indicators influencing transport sustainability***

The proposed list of transport sustainability indicators in this study was based on some selection criteria: relevant, representative and comprehensive, available, quantifiable, understandable by users, independent, and predictable. Selected indicators in previous studies have some problems that were overcome by this study; some of previous studies did not differentiate between transport sustainably final indicators and determinants. Some factors such as VKT, PKT, land-use mix, length of railways and main roads, proportion of residents with public transit services within 500 m (Jeon et al. 2005; Litman 2005; Nicolas et al. 2003; Zito et al. 2011), were considered as indicators; however they are not indicators, but intermediate determinants. This study differentiated between these two groups and use determinants like VKT, length of railways and main roads to quantify selected indicators such as the depletion of non-renewable resources, emissions and accessibility.

Some indicators were not included in this study such as road-way costs, costs of water pollution, and costs of wastes disposal. The reason for omitting these indicators is that available literature tried to quantify these costs per VKT. So these costs may not add extra value to selected indicators and consequently final index.

- ***Transportation environmental impact index (TEII), transportation social impact index (TSII), transportation economic impact index (TCII), and composite transport sustainability index (I_{CST})***

There are some limitations with previous studies considering transport sustainability:

- Most of sustainable transport studies, focused on providing long lists of indicators without any attempts to integrate them into a single index (Castillo et al. 2010; Jeon et al. 2005; Litman 2005; Nicolas et al. 2003).

- Studies that attempted to weight indicators, did not try to find the best approach for weighting. Normally, similar weighting method is selected because of ease of use (Haghshenas et al. 2012; Zito et al. 2011). Other studies, which tried to select different weights for different indicators, normally use AHP, which is subjective because of using experts' judgments (Shiau et al. 2012).

- Sustainability studies directly observed or measured indicators (D'Amico et al. 2012; Dur et al. 2010; Kolak et al. 2011; Zito et al. 2011), while there is no study tries to develop models for indicators quantifications.

This study overcomes the listed limitations:

- After selecting single indicators for three aspects, indicators for each aspect were aggregated into a single index. Single indices for each aspect were aggregated into a composite transport sustainability index (I_{CST}). So this study is a unique transport sustainability study at SLA level in Melbourne or even in Australia, which tries to develop a sustainability index for transport.

- The weighting method used in this study (PCA/FA) is the most appropriate approach for solving the problem of co-linearity among indicators, which provides a single weight for each indicator. So this thesis contributed to the body of knowledge by selecting a more suitable approach for indicators weighting.

- This study developed a land-use/transport interaction model, to quantify car ownership, VKT, and the proportion of car usage as functions of land-use and socio-economic factors. These travel behaviour measurements were used as determinants to quantify transport environmental, social, and economic indicators. So this study tried to develop a model for indicators quantification rather than directly observed or measured indicators.

➢ ***Transport sustainability indices for three urban-planning scenarios in Melbourne 2030***

While different attempts were made to quantify the effects of urban-planning scenarios on energy and emissions from transport, there is a lack of studies that try to quantify these effects on transport sustainability. One of the contributions of this thesis is analysing three urban-planning scenarios for Melbourne in 2030. As the input data and information was based on the government plan for 2030, this study provides a realistic view of the future. It helps to answer the question: 'How does urban-planning policy influence transport sustainability so that it would be beneficial for urban planning in Melbourne?'

8.4. Concluding remarks

The indicator approach adopted in this thesis enables progress toward transport sustainability to be monitored and any subsequent improvements to be measured. The developed base-case scenario predicted more sustainable transport in 2030 at household level. Better sustainability is the expected outcome of Victorian Government policy toward a more compact city with better transport links. The results of the comparison between urban-planning scenarios suggested that government policy toward high-density settlement in activity centres are an essential precondition for less car-dependent cities, and consequently more sustainable transport. Therefore, land-use policies supporting high densities and smaller distances between residences and facilities are a necessary ingredient of sustainability-oriented cities. These results are consistent with the available literature, which considered compactness essential for lower car ownership level, lower VKT, and higher public transport usage.

8.5. Recommendations for further studies

This study developed transport sustainability indices. However, further research needs to be carried out to enrich transport sustainability quantification in environmental, social, and economic dimensions. The following studies are recommended to improve transport sustainability indices:

- Considering the environmental, social, and economic impacts of freight transport: freight transport is a large contributor to emissions of CO_2 and mitigating its environmental impact is essential for a sustainable future. Despite the major role of freight transport on the environment and economy (NTC 2008), in the discussion of transport sustainability great attention is given to personal transport, i.e. car traffic, and freight transport is often neglected. So, there is a gap in transport sustainability evaluation related to freight transport. Considering passenger and freight transport at the same time in sustainability assessment would provide a more comprehensive transport sustainability index.

- Modelling noise pollution as one of the important environmental indicators: motorised vehicles are responsible for about 55% of the total noise in any urban environment. Traffic noise is one of the major environmental indicators of transport sustainability, which can cause health problems as well. For comprehensive noise pollution monitoring in a city, it is important to first assess various traffic characteristics such as traffic composition, speed, presence of mass transit system and congestion level (Rawat et al. 2009). Quantifying transport noise is complex and it is beyond the scope of this study. Considering this indicator may enrich the developed transport sustainability index.

- Using different weighting methods and comparing the results: this study selected PCA/FA as the most appropriate method for weighting indicators. As weighting indicators is one of the major steps in index development and affects the results, weighting method selection must be done with great consideration. Although this study presented the advantage of a selected weighting method to other widely used methods, it might be beneficial to develop transport sustainability indices using (testing) different weighting methods. Comparison of the results could illustrate the effects of weighting in index preparation and could justify selecting one weighting method as the most appropriate one for transport sustainability studies.

- Investigating the transferability of the models to other cities: this study selected two spatial scales in Melbourne as a case study, to check spatial transferability of the models. As the results indicated that modelling techniques are site specific, considering the same modelling techniques in other areas/cities would provide a strong evidence for transferability.

References

ABARE 1999, *Australian energy consumption and production, historical trends and projections*, Australian Bureau of Agriculture and Resource Economics.

ABS 2010, *Australian social trends- Australian households: the future*, Australian Bureau of Statistics.

Alberti, M. 1996, 'Measuring urban sustainability', *Environmental Impact Assessment Review*, vol. 16, no. 4, pp. 381-424.

Alford, G. & Whiteman, J. 2008, *Macro-urban form, transport energy use and greenhouse gas emissions: An investigation for Melbourne*, 31st Australian Transport Research Forum.

Apparicio, P., Abdelmajid, M., Riva, M. & Shearmur, R. 2008, 'Comparing alternative approaches to measuring the geographical accessibility of urban health services: Distance types and aggregation-error issues', *International Journal of Health Geographics*, vol. 7, no. 1, p. 7.

Apparicio, P. & Seguin, A. 2006, 'Measuring the accessibility of services and facilities for residents of public housing in Montreal', *Urban Studies*, vol. 43, no. 1, pp. 187-211.

ARRB 2007, *Development of crash rates for Australian roads*, Australian Road Research Board.

ATSB 2007, *Road crash casualties and rates, Australia, 1925 to 2005*, Australian Transport Safety Bureau.

Australian Government 2010, *National greenhouse accounts (NGA) factors*, Department of Climate Change and Energy Efficiency.

Awasthi, A. & Chauhan, S. S. 2011, 'Using AHP and Dempster-Shafer theory for evaluating sustainable transport solutions', *Environmental Modelling & Software*, vol. 26, pp. 787-96.

Banister, D., Watson, S. & Wood, C. 1997, 'Sustainable cities: transport, energy, and urban form', *Environment and Planning B*, vol. 24, pp. 125-44.

Barnes, G. & Langworthy, P. 2004, 'Per miles of operating automobiles and trucks transportation research record 1864', *Transportation Research Board*, pp. 71-7.

Beckerman, W. 2007, 'The chimera of ‘sustainable development’', *The Electronic Journal of Sustainable Development*, vol. 1, no. 1, pp. 17-26.

Behrends, S., Lindholm, M. & Woxenius, J. 2008, 'The impact of urban freight transport: A definition of sustainability from an actor's perspective', *Transportation Planning and Technology*, vol. 31, no. 6, pp. 693-713.

Bein, P. 1997, *Reviews of Transport 2021 costs of transporting people in the Lower Mainland* British Columbia Ministry of Transportation and Highways Planning Services Branch.

BITRE 2009, *Road crash costs in Australia 2006*, Bureau of Infrastructure, Transport and Regional Economics.

Blattberg, R. C., Kim, B. & Neslin, S. A. 2008, *Database marketing: Analyzing and managing customers*, International Series in Quantitative Marketing, Springer.

Boarnet, M. G. & Sarmiento, S. 1998, 'Can land-use policy really affect travel behaviour? A study of the link between non-work travel and land-use characteristics', *Urban Studies*, vol. 35, no. 7, pp. 1155-69.

BREE 2010, *Australian petroleum statistics*, Bureau of Resources and Energy Economics.

Breheny, M. 1995, 'The compact city and transport energy consumption', *Transactions of the Institute of British Geographers*, vol. 20, no. 1, pp. 81-101.

Breheny, M. J. 1992, *Sustainable development and urban form*, Pion London.

Brindle, R., Houghton, N. & Sheriden, G. 1999, 'Transport generated air pollution and its health impacts—a source document for local government, research report ARR 336', *ARRB Transport Research, Victoria*.

BTCE 1992, *Social cost of transport accidents in Australia*, Bureau of Transport and Communications Economics.

BTE 2000, *Road crash costs in Australia*, Bureau of Transport Economics.

BTRE 2005, *Health impacts of transport emissions in Australia: Economic costs*, Department of Transprt and Regional Services.

Button, K., Fowkes, A. & Pearman, A. 1980, 'Disaggregate and aggregate car ownership forecasting in Great Britain', *Transportation Research Part A: General*, vol. 14, no. 4, pp. 263-73.

Camagni, R., Gibelli, M. C. & Rigamonti, P. 2002, 'Urban mobility and urban form: the social and environmental costs of different patterns of urban expansion', *Ecological Economics*, vol. 40, no. 2, pp. 199-216.

Campos, V. B. G., Ramos, R. A. R. & De Miranda e Silva Correia, D. 2009, 'Multi-criteria analysis procedure for sustainable mobility evaluation in urban areas', *Journal of Advanced Transportation*, vol. 43, no. 4, pp. 371-90.

Carey, A. 2013, 'New trams arrive, but not on schedule', *The Age*, 1st of July.

Castillo, H. & Pitfield, D. E. 2010, 'ELASTIC-A methodological framework for identifying and selecting sustainable transport indicators', *Transportation Research Part D: Transport and Environment*, vol. 15, no. 4, pp. 179-88.

Cervero, R. 1996, 'Mixed land-uses and commuting: evidence from the American Housing Survey', *Transportation Research Part A: Policy and Practice*, vol. 30, no. 5, pp. 361-77.

Chaparro, F., Salinas-Jimenez, J. & Smith, P. 1997, 'On the role of weight restrictions in data envelopment analysis', *Journal of Productivity Analysis*, vol. 8, pp. 215-30.

Charnes, A. 1994, *Data envelopment analysis: theory, methodology, and application*, Springer.

Cherchye, L., Moesen, W. & Puyenbroeck, T. 2004, 'Legitimately diverse, yet comparable: On synthesizing social inclusion performance in the EU', *Journal of Common Market Studies*, vol. 42, no. 5, pp. 919-55.

Cherchye, L., Moesen, W., Rogge, N. & Puyenbroeck, T. V. 2007, 'An introduction to ‘benefit of the doubt’ composite indicators', *Social Indicators Research*, vol. 82, no. 1, pp. 111-45.

City of Melbourne 2011, *Transport strategy update 2011, Planning for future growth*, City of Melbourne.

City of Melbourne 2013, *Population forecast*, <http://forecast2.id.com.au/default.aspx?id=128&pg=5150>.

Coffey 2003, *Fuel quality and vehicle emissions standards-Cost benefit analysis*, Coffey Geosciences PTY LTD.

Corpuz, G., McCabe, M. & Ryszawa, K. 2006, *The development of a Sydney VKT regression model*, 29th Australian Transport Research Forum, Gold Coast.

D'Amico, P., Di Martino, F. & Sessa, S. 2012, 'A GIS as a decision support system for planning sustainable mobility in a case-study', *Contemporary Engineering Sciences*, vol. 5, no. 1, pp. 9-23.

Dargay, J. M. & Hanly, M. 2003, *The impact of land use patterns on travel behaviour*, European Transport Conference, France.

Davidson, P. 2011, *A new approach to transport modelling-the Stochastic Segmented Slice Simulation (4S) model and its recent applications*, Australian Transport Research Forum, Adelaide, Australia.

De Jong, G., Fox, J. & Daly, A. 2004, 'Comparison of car ownership models', *Transport Review*, vol. 24, no. 4, pp. 379-408.

DeCoster, J. 1998, *Overview of factor analysis*, Retrieved May 2006, <www.stat-help.com/notes.html>.

Dieleman, F. M., Dijst, M. & Burghouwt, G. 2002, 'Urban form and travel behaviour: micro-level household attributes and residential context', *Urban Studies*, vol. 39, no. 3, pp. 507-27.

Dobranskyte-Niskota, A., Perujo, A. & Pregl, M. 2007, *Indicators to assess sustainability of transport activities*, JRC European Commission.

Doody, D., Kearney, P., Barry, J., Moles, R. & O'Regan, B. 2009, 'Evaluation of the Q-method as a method of public participation in the selection of sustainable development indicators', *Ecological Indicators*, vol. 9, no. 6, pp. 1129-37.

DOT 2007, *Victorian Integrated Survey of Travel and Activity 2007 (VISTA07)*.

Dowling, J. 2013, 'New stations, longer trains tipped for Melbourne rail', *The Age*, 26th March.

DPIE & DHSH 1997, *Rural, remote and metropolitan areas classification*, Department of Primary Industries and Energy, Department of Human Services and Health.

DTPLI 2002, *Melbourne 2030, Planning for sustainable growth*, Department of Transport, Planning and Local Infrastructure

DTPLI 2012, *Victoria in future 2012, population and household projections 2011-2031 for Victoria and its regions*, Department of Transport, Planning and Local Infrastructure.

Dur, F., Yigitcanlar, T. & Bunker, J. 2010, *Towards sustainable urban futures: evaluating urban sustainability performance of the Gold Coast, Australia*, 14th IPHS Conference, Istanbul, Turkey.

EA 1999, *Sustainable transport: responding to the challenges*, The Institution of Engineers, Australia.

Edara, P. 2003, *Mode choice modeling using artificial neural networks*, Virginia Polytechnic Institute and State University.

EPA 2000, *Melbourne mortality study: Effects of ambient air pollution on daily mortality in Melbourne 1991-1996*, Environmental Protection Authority.

ESRI 1999, *How fuzzy memebership works*, 2013, <http://help.arcgis.com/en/arcgisdesktop/10.0/help/index.html#//009z000000rz000000.htm>.

Faulkner, H. W. & French, S. 1983, *Geographic remoteness: Conceptual and measurement problems*, Bureau of Transport Economics.

Fishman, E., Ker, I., Garrard, J., Litman, T. & Rissel, C. 2011, *Cost and health benefit of active transport in Queensland: Stage two report - Evaluation framework and values*, CATALYST for Health Promotion Queensland.

Forkenbrock, D. J. & Weisbrod, G. E. 2001, *Assessing the social and economic effects of transportation projects*, National Academy Press.

Freudenberg, M. 2003, *Composite indicators of country performance: a critical assessment*, OECD Publishing.

Geurs, K. & Wee, B. 2004, 'Accessibility evaluation of land-use and transport strategies: review and research directions', *Journal of Transport Geography*, vol. 12, pp. 127-40.

Gilbert, R., Irwin, N., Hollingworth, B. & Blais, P. 2002, *Sustainable transportation performance indicators*, Annual Conference of the Transportation Association of Canada

GISCA 2011, *Accessibility remoteness index of Australia (ARIA) review*, National Centre for Social Applications of Geographic Information Systems.

Giuliano, G. & Dargay, J. 2006, 'Car ownership, travel and land use: a comparison of the US and Great Britain', *Transportation Research Part A: Policy and Practice*, vol. 40, no. 2, pp. 106-24.

Gomez-Limon, J. A. & Riesgo, L. 2008, *Alternative approaches on constructing a composite indicator to measure agricultural sustainability*, European Association of Agricultural Economists, 107th Seminar, Seville, Spain.

Gordon, P. & Richardson, H. W. 1989, 'Gasoline consumption and cities: a reply', *Journal of the American Planning Association*, vol. 55, no. 3, pp. 342-6.

Green, C. & Argue, T. 2011, *Summary guidelines and standards for the planning of social facilities and recreational spaces in metropolitan Area*, CSIR.

Habibpour Gatabi, K. & Safari Shali, R. 2010, *Comprehensive manual for using SPSS in survey researches*, Motofakeran.

Haghshenas, H. & Vaziri, M. 2012, 'Urban sustainable transportation indicators for global comparison', *Ecological Indicators*, vol. 15, no. 1, pp. 115-21.

Hamilton, B. 2003, *ACT transport demand elasticities study*, Department of Urban Services.

Hellman, M. 1968, 'Fuzzy Logic Introduction', *Info. & Ctl*, vol. 12, pp. 94-102.

Hess, D. & Ong, P. 2002, 'Traditional neighborhoods and automobile ownership', *Transportation Research Records*, vol. 1805, pp. 35-44.

Holden, E. & Norland, I. T. 2005, 'Three challenges for the compact city as a sustainable urban form: household consumption of energy and transport in eight residential areas in the greater Oslo region', *Urban Studies*, vol. 42, no. 12, pp. 2145-66.

Hunt, J. D., Kriger, D. S. & Miller, E. 2005, 'Current operational urban land use–transport modelling frameworks: A review', *Transport Reviews*, vol. 25, no. 3, pp. 329-76.

Janic, M. 2006, 'Sustainable transport in the European Union: A review of the past research and future ideas', *Transport Reviews*, vol. 26, no. 1, pp. 81-104.

Jeon, C. M. & Amekudzi, A. 2005, 'Addressing sustainability in transportation systems: definitions, indicators, and metrics', *Journal of Infrastructure Systems*, vol. 11, pp. 31-50.

Jollands, N. 2003, *The usefulness of aggregate indicators in policy making and evaluation: a discussion with application to eco-efficiency indicators in New Zealand*, http://hdl.handle.net/1885/41033.

Jollands, N., Lermit, J. & Patterson, M. 2003, 'The usefulness of aggregate indicators in policy making and evaluation: a discussion with application to eco-efficiency indicators in New Zealand', *Economics and Environment Network, Australian National University*.

Kahn Ribeiro, S., Kobayashi, S., Beuthe, M., Gasca, J., Greene, D., Lee, S., Muromachi, Y., Newton, P. J., Plotkin, S., Sperling, D., Wit, R. & Zhou, P. J. 2007, *Transport and its Infrastructure*, Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.

Kanaroglou, P. S. & South, R. 2001, 'Can urban form affect transportation energy use and emissions?', *Energy Studies Review*, vol. 9, no. 2, p. 5.

Kao, C. & Hung, H. T. 2005, 'Data envelopment analysis with common weights: The compromise solution approach', *Journal of the Operational Research Society*, vol. 56, no. 10, pp. 1196-203.

Kellett, J. & Rofe, M. 2009, *Creating active communities: How can open and public spaces in urban and suburban environments support active living?*, Institute for sustainable systems and technologies, University of South Australia.

Khan, A. A. 1992, 'An integrated approach to measuring potential spatial access to health care services', *Socio-Economic Planning Sciences*, vol. 26, no. 4, pp. 275-87.

Kitamura, R., Mokhtarian, P. L. & Laidet, L. 1997, 'A micro-analysis of land use and travel in five neighborhoods in the San Francisco Bay Area', *Transportation*, vol. 24, no. 2, pp. 125-58.

Kline, P. 1994, *An easy guide to factor analysis*, Routledge.

Kobos, P. H., Erickson, J. D. & Drennen, T. E. 2003, 'Scenario analysis of Chinese passenger vehicle growth', *Contemporary Economic Policy*, vol. 21, no. 2, pp. 200-17.

Kolak, O. I., Akın, D., Birbil, Ş. I., Feyzioğlu, O. & Noyan, N. 2011, 'Multicriteria sustainability evaluation of transport networks for selected European countries', *Lecture Notes in Engineering and Computer Science*, vol. 2190, no. 1, pp. 117-22.

Krajnc, D. & Glavič, P. 2005, 'A model for integrated assessment of sustainable development', *Resources, Conservation and Recycling*, vol. 43, no. 2, pp. 189-208.

Künzli, N. 1999, *Health costs due to road traffic-related air pollution: An impact assessment project of Austria, France and Switzerland: Prepared for the WHO Ministerial Conference on Environment and Health, London, June, 1999: Air pollution attributable cases: Technical Report on Epidemiology*, Eidgenössisches Department für Umwelt, Verkehr, Energie und Kommunikation.

Kunzli, N., Kaiser, R., Medina, S., Studnicka, M., Oberfeld, G. & Horak, F. 1999, *Health costs due to road traffic-related air pollution, An impact assessment project of Austria, France and Switzerland*, Third Ministerial Conference for Environment and Health, London.

Legacy, C., Glover, L. & Low, N. 2007, *Investigation of the greenhouse impacts of different transport modes in Australian cities*, Australasian Centre for the Governance and Management of Urban Transport (GAMUT), The University of Melbourne, Victoria 3010, Australia (an initiative of the Volvo Research and Educational Foundations).

Levett, R. 1998, 'Sustainability indicators—integrating quality of life and environmental protection', *Journal of the Royal Statistical Society: Series A (Statistics in Society)*, vol. 161, no. 3, pp. 291-302.

Levinson, D. & Gillen, D. 1998, 'The full cost of intercity highway transportation', *Transportation Research*, vol. 3, no. 4, pp. 207-23.

Limanond, T., Jomnonkwao, S. & Srikaew, A. 2011, 'Projection of future transport energy demand of Thailand', *Energy Policy*, vol. 39, no. 5, pp. 2754-63.

Lindsey, M., Schofer, J. L., Durango-Cohen, P. & Gray, K. A. 2011, 'The effect of residential location on vehicle miles of travel, energy consumption and greenhouse gas emissions: Chicago case study', *Transportation Research Part D: Transport and Environment*, vol. 16, no. 1, pp. 1-9.

Litman, T. 2003, *Transportation cost and benefit analysis: techniques, estimates and implications*, Victoria Transport Policy Institute.

Litman, T. 2005, *Well-measured-developing indicators for comprehensive and sustainable transport planning*, Victoria Transport Policy Institute.

Litman, T. 2009, *Sustainable transportation indicators: A recommended research program for developing sustainable transportation indicators and data*, Transportation Research Board 88th Annual Meeting, Washington DC.

Litman, T. 2013, *Evaluating public transport benefits and costs*, Victoria Transport Policy Institute.

Lotfi, S. & Koohsari, M. 2009, 'Measuring objective accessibility to neighbourhood facilities in the city (A case study: Zone 6 in Tehran, Iran)', *Cities*, vol. 26, pp. 133-40.

Loucks, D. 1997, 'Quantifying trends in system sustainability', *Hydrological Science Journal*, vol. 42, no. 4, pp. 513-30.

Makri, M.-C. & Folkesson, C. 1999, *Accessibility measures for analyses of land use and travelling with geographical information systems*, 2nd KFB-Research Conference.

Maroko, A. R., Maantay, J. A., Sohler, N. L., Grady, K. L. & Arno, P. S. 2009, 'The complexities of measuring access to parks and physical activity sites in New York City: A quantitative and qualitative approach', *International Journal of Health Geographics*, vol. 8, no. 1, p. 34.

McKibbin, M. 2011, *The influence of the built environment on mode choice–evidence from the journey to work in Sydney*, Australian Transport Research Forum, Adelaide, Australia.

Miller, E. J. & Ibrahim, A. 1998, 'Urban form and vehicular travel: some empirical findings', *Transportation Research Record: Journal of the Transportation Research Board*, vol. 1617, no. 1, pp. 18-27.

Murat, Y. S. & Ceylan, H. 2006, 'Use of artificial neural networks for transport energy demand modeling', *Energy Policy*, vol. 34, no. 17, pp. 3165-72.

Næss, P. 2009, 'Residential location, travel behaviour, and energy use: Hangzhou metropolitan area compared to Copenhagen', *Indoor and Built Environment*, vol. 18, no. 5, pp. 382-95.

Nardo, M., Saisana, M., Saltelli, A. & Tarantola, S. 2005, *Tools for composite indicators building*, Institute for the Protection and Security of Citizen.

Naumann, R. D., A., Zaloshnja, E., Lawrence, B. & Miller, T. 2010, 'Incidence and total lifetime costs of motor vehicle-related fatal and nonfatal injury by road user type, United States,2005', *Traffic Injury Prevention*, vol. 11, no. 353-360.

Newman, P. & Kenworthy, J. R. 1991, 'Transport and urban form in thirty two of the world's principal cities', *Transport Reviews*, vol. 11, no. 3, pp. 249-72.

Newton, P. W. 1997, *Re shaping cities for a more sustainable future, exploring the link between urban form, air quality, energy and greenhouse gas emissions*, Australian Housing and Urban Research Institute.

Nicolas, J. P., Pochet, P. & Poimboeuf, H. 2003, 'Towards sustainable mobility indicators: application to the Lyons conurbation', *Transport Policy*, vol. 10, no. 3, pp. 197-208.

Nijkamp, P., Verhoef, E., Ubbels, B. & Rodenburg, C. 2011, *Sustainable mobility*, University Amsterdam, Faculty of Economics, Business administration and econometrics.

NPi 2002, *Emission estimation technique manual for combustion engine*, National Pollutant Inventory.

NPi 2008, *Emission estimation technique manual for combustion engine*, National Pollutant Inventory.

NTC 2008, *Freight transport in a carbon constrained economy*, National Transport Commission.

OECD 1996, *Towards sustainable transportation*, The Vancouver Conference, Vancouver, British Columbia.

OECD 2008, *Handbook on constructing composite indicators, methodology and user guide*, Organisation for Economic Co-operation and Development

Öğüt, K. S. 2006, 'Modeling car ownership in Turkey using fuzzy regression', *Transportation Planning and Technology*, vol. 29, no. 3, pp. 233-48.

Ostro, B. 2004, 'Outdoor air pollution: assessing the environmental burden of disease at national and local levels', *Environmental Burden of Disease Series*, vol. 5.

Özkaynak, H. & Thurston, G. D. 1987, 'Associations between 1980 US mortality rates and alternative measures of airborne particle concentration', *Risk Analysis*, vol. 7, no. 4, pp. 449-61.

Paravantis, J. & Georgakellos, D. 2007, 'Trends in energy consumption and carbon dioxide emissions of passenger cars and buses', *Technological Forecasting and Social Change*, vol. 74, no. 5, pp. 682-707.

Peden, M., Scurfield, R., Sleet, D., Mohan, D., Hyder, A., Jarawan, E. & Mathers, C. 2004, *World report on road traffic injury prevention*, World Health Organization Geneva.

PI 2001, *Alberta GPI Blueprint Report*, Pembina Institute.

Pitot, M., Yigitcanlar, T., Sipe, N. & Evans, R. 2006, Land use & public transport accessibility Index (LUPTAI) tool: The development and pilot application of LUPTAI for the Gold Coast, paper presented Planning and Transport Research Centre (PATREC).

Pongthanaisawan, J. & Sorapipatana, C. 2010, 'Relationship between level of economic development and motorcycle and car ownerships and their impacts on fuel consumption and greenhouse gas emission in Thailand', *Renewable and Sustainable Energy Reviews*, vol. 14, no. 9, pp. 2966-75.

PWC 2011, *A walking strategy for NSW- Assessing the economic benefits of walking*, PricewaterhouseCoopers.

RACV 2011, *Driving your dollars*, Royal Automobile Club of Victoria.

RACV 2012, *Driving your dollars*, Royal Automobile Club of Victoria.

Rawat, K. & Katiyar, V. K. 2009, 'Mathematical modeling of environmental noise impact', *Indian Journal of Biomechanics*, pp. 75-81.

Rickwood, P. 2009, The impact of physical planning policy on household energy use and greenhouse emissions, University of Technology, Sydney.

Rickwood, P., Glazebrook, G. & Searle, G. 2008, 'Urban structure and energy—a review', *Urban Policy and Research*, vol. 26, no. 1, pp. 57-81.

Rodriguez, D. A., Targa, F. & Aytur, S. A. 2006, 'Transport implications of urban containment policies: A study of the largest twenty-five US metropolitan areas', *Urban Studies*, vol. 43, no. 10, pp. 1879-97.

Rossi, R., Gastaldi, M. & Gecchele, G. 2013, 'Comparison of fuzzy-based and AHP methods in sustainability evaluation: A case of traffic pollution-reducing policies', *European Transport Research Review*, vol. 5, pp. 11-26.

Ryley, T. 2006, 'Use of non-motorised modes and life stage in Edinburgh', *Journal of Transport Geography*, vol. 14, no. 5, pp. 367-75.

Sahely, H. R., Kennedy, C. A. & Adams, B. J. 2005, 'Developing sustainability criteria for urban infrastructure systems', *Canadian Journal of Civil Engineering*, vol. 32, no. 1, pp. 72-85.

Saisana, M. 2011, *Weighting methods*, Seminar on Composite Indicators: From Theory to Practice, Ispra, Italy.

Saisana, M. & Tarantola, S. 2002, *State of the art report on current methodologies and practices for composite indicator development*, Institute for the Protection and Security of the Citizen.

Scheurer, J. 2010, *Scenarios for future land use-transport integration in the city of Melbourne (and beyond)*, RMIT-AHURI Research Centre.

Shiau, T. & Peng, Q. 2012, 'Mode-based transport sustainability: A comparative study of Taipei and Kaohsiung cities', *Journal of Sustainable Development*, vol. 5, no. 10, pp. 68-76.

Shoup, D. 2005, *The highest gost of free parking*, Planners Press.

Shunping, J., Hongqin, P., Shuang, L. & Xiaojie, Z. 2009, 'Review of transportation and energy consumption related research', *Journal of Transportation Systems Engineering and Information Technology*, vol. 9, no. 3, pp. 6-16.

Soltani, A. & Allan, A. 2005, *A computer methodology for evaluating urban areas for walking, cycling and transit suitability: Four case studies from Suburban Adelaide*, 8th

Computers in Urban Planning and Urban Management Conference, London, United Kingdom.

Soltani, A. & Somenahalli, S. 2005, *Household vehicle ownership: Does urban structure matter?*, 28th Australian Transport Research Forum, Sydney.

Southworth, F. 1995, *A technical review of urban land use - transportation models as tools for evaluating vehicle travel reduction strategies*, MARTIN MARIETTA ENERGY SYSTEMS.

SPSS Forecasting 17.0, viewed 23/08/2013 <http://www.docs.is.ed.ac.uk/skills/documents/3663/SPSSForecasting17.0.pdf>.

State Government Victoria 2012, *Melbourne, let's talk about the future*.

Sydneybuses 2014, *Chartering a bus*, NSW Transport Buses, <http://www.sydneybuses.info/chartering-a-bus/chartering-a-bus.htm>.

Tanguay, G. A., Rajaonson, J., Lefebvre, J. F. & Lanoie, P. 2010, 'Measuring the sustainability of cities: An analysis of the use of local indicators', *Ecological Indicators*, vol. 10, no. 2, pp. 407- 18.

Tao, C. C. & Hung, C. C. 2003, 'A comparative approach of the quantitative models for sustainable transportation', *Journal of the Eastern Asia Society for Transportation Studies*, vol. 5, pp. 3329-44.

Timmermans, H. 2003, *The saga of integrated land use-transport modeling: How many more dreams before we wake up*, 10th International Conference on Travel Behaviour Research, Lucerne.

TRB 2004, *Integrating sustainability into the transportation planning process*, Introducing Sustainability into Surface Transportation Planning, Baltimore, Maryland.

Trubka, R., Newman, P. & Bilsborough, D. 2008, *Assessing the costs of alternative development paths in Australian cities*, Curtin University.

Trubka, R., Newman, P. & Bilsborough, D. 2010, 'The costs of urban sprawl - predicting transport greenhouse gases from urban form parameters', *Environment Design Guide*, pp. 1-16.

VAG 2005, *Franchising Melbourne's train and tram system*, Victorian Auditor General.

Vandenbulcke, G., Steenberghen, T. & Thomas, I. 2009, 'Mapping accessibility in Belgium: a tool for land-use and transport planning?', *Journal of Transport Geography*, vol. 17, no. 1, pp. 39-53.

Verhoef, E., Ubbels, B., Rodenburg, C. & Nijkamp, P. 2001, 'Sustainable mobility', *Research Memorandum*, vol. 14.

VTPI 2010, *Sustainable transport and TDM, Planning that balances economic, social and ecological objectives*, Victoria Transport Policy Institute.

Wang, F. & Luo, W. 2005, 'Assessing spatial and nonspatial factors for healthcare access: towards an integrated approach to defining health professional shortage areas', *Health & Place*, vol. 11, no. 2, pp. 131-46.

Wang, J., Knipling, R. & Blincoe, L. 1999, 'The dimensions of motor vehicle crash risk', *Journal of Transportation and Statistics*, pp. 19-43.

Wang, M. 2008, *Estimation of energy efficiencies of U.S. petroleum refineries*, Centre for Transportation Research, Argonne National Laboratory.

Webster, F. V. & Paulley, N. J. 1990, 'An international study on land use and transport interaction', *Transport Reviews*, vol. 10, no. 4, pp. 287-308.

Wegener, M. 1994, 'Operational urban models state of the art', *Journal of the American Planning Association*, vol. 60, no. 1, pp. 17-29.

Whelan, G., Crockett, J. & Vitouladiti, S. 2010, *A New Model of Car Ownership in London: Geo-Spatial Analysis of Policy Interventions*, European Transport conference

Witten, K., Exeter, D. & Field, A. 2003, 'The quality of urban environments: Mapping variation in access to community resources', *Urban Studies*, vol. 40, no. 1, pp. 161-77.

Yigitcanlar, T., Fabian, L. & Coiacetto, E. 2008, 'Challenges to urban transport sustainability and smart transport in a tourist city: The Gold Coast', *The Open Transportation Journal*, vol. 2, pp. 29-46.

Zegras, C. 2006, *Sustainable transport indicators and assessment methodologies*, Biannual Conference and exhibit of the Clean Air Initiative for Latin American Cities, Brazil.

Zhang, X., Lu, H. & Holt, J. 2011, 'Modeling spatial accessibility to parks: a national study', *International Journal of Health Geographics*, vol. 10, no. 31.

Zhang, Y. & Guindon, B. 2006, 'Using satellite remote sensing to survey transport-related urban sustainability Part 1: Methodologies for indicator quantification', *International Journal of Applied Earth Observation and Geoinformation*, vol. 8, no. 3, pp. 149-64.

Zhou, P., Ang, B. & Poh, K. 2007, 'A mathematical programming approach to constructing composite indicators', *Ecological Economics*, vol. 62, no. 2, pp. 291-7.

Zito, P. & Salvo, G. 2011, 'Toward an urban transport sustainability index: an European comparison', *European Transport Research Review*, vol. 3, pp. 1-17.

Appendix 1. Petroleum refinery efficiency in Melbourne

The current road transport system depends on non-renewable fuels. The rate of consumption of non-renewable fuels is projected to grow as travel increases. Transport planning should address transport negative impacts, including depletion of non-renewable fuels (TRB 2004). In this study the petroleum refinery efficiency is calculated using Equation 1 (Wang 2008):

$$\text{Petroleum refinary efficiency} = \frac{\text{Energy of all petroleum products}}{\text{Energy of crude oil inputs}} \tag{1}$$

Table 1 shows litres of crude oil input and product outputs of petroleum refineries and their energy contents in Australia. So based on Table 1, total input energy is 1,464,740,968 GJ and total energy for outputs is 1,334,371,138 GJ. According to Equation 1, petroleum refinery efficiency in Melbourne is:

$$\frac{1334371138}{1464740968} = 0.91 \text{ or } 91\%$$

Based on models presented in Chapter 3, total energy consumption from transport is 96,521,823,505 MJ in 2006. Considering refinery efficiency (91%), for the production of this amount of energy 1.06E+11 MJ of crude oil was used, which is equal to 3.21E+14 litres of crude oil.

Table 1.Petroleum refinery's input and outputs in Australia (ABARE 1999; Australian Government 2010; BREE 2010)

Input		
	Production (ML)	**Energy content (GJ/KL)**
Crude oil	37681.2	38.8
Output		
	Production (ML)	**Energy content (GJ/KL)**
LPG	1203.6	25.7
Automotive gasoline	16771.2	34.2
Aviation gasoline	103.7	33.1
Aviation turbine fuel	5340.8	35.9
Heating oil	34.5	37.3
Automotive diesel oil	11719.4	38.6
Industrial & marine diesel fuel	2.9	39.6
Fuel oil	846.6	39.7
petroleum based greases	74.4	38.8
Bitumen	690.2	44.0
Other products	412.4	34.4

Appendix 2. Land-use/transport interaction model at CCD level

To evaluate models transferability over different spatial scale, modelling was repeated for CCD level and compared with the results of SLA level. One of the land-use/transport models applied in this thesis was computational, while two other were statistical. The first sub-model was a car-ownership model, as car ownership is known to influence travel decisions. The second sub-model provided an estimate of the number of kilometres travelled by cars. The results of the second sub-model influence the estimate of public transport travel in the final sub-model. As required information for developing the models were not available for all CCD in Melbourne, some CCDs that their information was available through VISTA07 were used as representatives of CCD level.

As described in Chapter 3, car ownership, VKT, and modal split could be estimated using selected socio-economic and land-use factors. Before using different modelling techniques, some correlation analyses were undertaken between car ownership, VKT, percentage of trips by car as travel behaviour measurements, and selected land use and socio-economic factors (Table 1). The correlation coefficients, which range from -1 to +1, show the strength of association between selected socio-economic factors, land-use factors, and travel behaviour measurements. Higher correlation coefficients show stronger link between variables. The sign of the coefficient denotes the trend of impact; the positive coefficient means the travel behaviour measurement has the same trend as the selected socio-economic and land-use factors. The significant level is also provided in Table 1. Statistical significance is the probability that a relationship between factors is not likely due to just chance alone. Significant level usually set at 0.05 (5%) or 0.01 (1%). Significant level of 0.05 means that findings have 5% chance of not being true, or 95% chance of being true (see 'CCD model\ linear regression\ correlation.spv' in Appendix 3). It is worth noting that the units of the factors do not influence correlation coefficients. Moreover, considering different forms of dependent and independent variables showed that ln VKT, ln modal split and square root of household annual income, provided stronger correlation relationships. So from now onward, these transformed variables will be used in the analyses.

Table 1. Correlation among travel behaviour indicators, land-use and socio-economic factors in Melbourne (2006)

	Car ownership (-)	**VKT (km)**	**Trips by car (%)**
Household annual income ($)	0.15**	0.12**	0.48**
Proportion of couples with children to other household types	0.57**	0.35**	0.12*
Population density (person/ha)	-0.21**	-0.36**	-0.42**
Access to public transport (km)	0.11*	0.22**	0.14**
Proportion of detached houses to other dwelling types	0.32**	N/A	N/A
Distance from the CBD (km)	0.08	0.33**	N/A
Walkability	-0.21**	-0.21**	-0.35**
Car ownership (-)	1	0.62**	0.26**
Land area of SLA (km^2)	N/A	0.17**	0.14**
** Level of significance = 0.01, * Level of significance = 0.05			

Based on the correlation analyses, car ownership, VKT and percentage of trips by car can be estimated as functions of land-use and socio-economic factors. Three different modelling techniques were attempted to estimate car ownership, VKT and percentage of trips by car based on land-use and socio-economic factors that have significant correlations with travel behavior measurements.

2.1. Linear regression land-use/transport interaction model

To see if a linear relationship is valid between selected socio-economic, land-use factors, and travel behaviour measurements, regression analysis was used for developing car ownership, VKT and modal split models. Different parameters are used to evaluate regression analysis. The sign of the coefficients denotes the trend of impact; the positive coefficient means the dependent variable has the same trend as the independent variable. Moreover, R^2 shows how well a regression model fits the data and how much of the variance in the dependent variable is explained by the combination of independent variables. The closer R^2 is to 1, the better the model fits. Significance level or p-value is another important parameter in regression analysis. It tests the null hypothesis that the regression coefficient is equal to zero (i.e. there is no relationship between dependent and independent variables). A low p-value (<0.05) indicates that the null hypothesis can be rejected. With a p-value of 5% (or .05) there is only a 5% chance that results would have come up by chance. Co-linearity in regression analysis refers to a condition in which dependencies among the independent variables result in incorrect estimate. Variance inflation factor (VIF) quantifies the severity of co-linearity in regression analysis. A VIF larger than 2 shows co-linearity among independent variables. A normal VIF threshold for highest co-linearity among independent variables is 5.

- ***Car ownership***

  Car ownership, as a dependent variable, was modelled using a linear regression analysis as functions of selected land-use and socio-economic factors (Table 2) (see 'CCD level\ linear regression\car ownership.spv, car ownership regression.xlsx in Appendix 3).

Table 2. Linear regression analysis for car ownership in Melbourne (2006)

Independent variables	Standardised coefficients	p-value	Variance inflation factor
Constant (-)	5.584	N/A	N/A
Household annual income ($)	-0.03	0.55	1.08
Proportion of couples with children to other household types	0.54	0.00	1.07
Population density (person/ha)	-0.05	0.39	1.27
Access to public transport (km)	0.05	0.28	1.17
Proportion of detached houses to other dwelling types	0.12	0.03	1.31
Walkability (-)	-0.05	0.37	1.23
Adjusted $R^2 = 0.34$			

- ***VKT***

  A linear regression model was used to estimate household VKT. Regression coefficients are presented in Table 3 (see 'CCD level\ linear regression\ vkt regression.spv, vkt model.xlsx' in Appendix 3).

Table 3. Linear regression analysis for VKT in Melbourne (2006)

Independent variables	Standardised coefficients	p-value	Variance inflation factor
Constant (%)	-4.11	N/A	N/A
Household annual income ($)	0.03	0.46	1.05
Proportion of couples with children to other household types	0.05	0.38	1.57
Access to public transport (km)	0.01	0.90	1.37
Distance to the CBD (km)	0.29	0.00	1.44
Walkability (-)	0.06	0.24	1.20
Car ownership (-)	0.59	0.00	1.51
Area of SLA (km^2)	0.08	0.07	1.14
Adjusted R^2=0.46			

- ***Modal split***

The dependent variable for this regression analysis is defined as the percentage of trips by cars (see 'CCD level- linear regression\ mode regression.spv, modal split regression.xlsx' in Appendix 3).

Table 4. Linear regression analysis for percentage of trip by personal car (2006)

Independent variables	**Standardised coefficients**	**p-value**	**Variance inflation factor**
Constant (%)	-1.10	N/A	N/A
Household annual income ($)	0.24	0.00	1.07
Proportion of couples with children to other household types (-)	-0.05	0.46	1.50
Population density (person/ha)	-0.23	0.00	1.34
Access to public transport (km)	0.01	0.81	1.23
Walkability (-)	-0.13	0.02	1.13
Car ownership (-)	0.13	0.04	1.52
Area of SLA (km^2)	-0.02	0.71	1.25
Adjusted R^2=0.17			

Some of the linear regression coefficients are conflicting with the results of correlations. For example, while area of SLA is positively correlated with modal split, the sign of regression coefficient in modal split model is negative. This is because of co-linearity among selected independent variables. One suitable strategy for solving co-linearity problem is using stepwise regression that removes independent variables one at a time automatically until the VIF values for the variables remaining are all acceptable (<2). The results of stepwise regression for car ownership, VKT, and modal split are shown in Tables 5, 6, 7 (see 'CCD level\ linear regression\ car ownership.spv, car ownership regression.xlsx, vkt regression.spv, vkt model.xlsx, mode regression.spv, modal split regression.xlsx' in Appendix 3):

Table 5. Stepwise linear regression for car ownership in Melbourne (2006)

Independent variables	**Standardised coefficients**	**p-value**	**Variance inflation factor**
Constant (-)	1.38	N/A	N/A
Proportion of couples with children to other household types (-)	0.53	0.00	1.05
Proportion of houses to other dwelling types (-)	0.16	0.00	1.05
Adjusted R^2 = 0.34			

Table 6. Stepwise linear regression for VKT in Melbourne (2006)

Independent variables	Standardised coefficients	p-value	Variance inflation factor
Constant (km)	1.97	N/A	N/A
Car ownership (-)	0.61	0.00	1.00
Distance from CBD (km)	0.29	0.00	1.00
Adjusted R^2=0.46			

Table 7. Stepwise linear regression for percentage of trips by personal car

Independent variables	Standardised coefficients	p-value	Variance inflation factor
Constant (%)	-1.00	N/A	N/A
Population density (person/ha)	-0.22	0.00	1.13
Household annual income ($)	0.24	0.00	1.06
Walkability (-)	-0.13	0.02	1.08
Car ownership (-)	0.11	0.05	1.03
Adjusted R^2=0.18			

2.2. Log-linear regression

As there was a poor linear relationship between travel behaviour measurements, socio-economic, and land-use factors, log-linear models might be a suitable modelling technique in CCD level in Melbourne. This hypothesis was tested by modelling car ownership, VKT and modal split using log-linear regression model.

- ***Car ownership***

  A log-linear model is a model that simply analyses the dependent and the independent variables in logarithm form. The estimated coefficients illustrate the elasticity of the dependent variable with respect to the independent variables. The general form of a log-linear regression equation can be written as (Limanond, Jomnonkwao & Srikaew 2011):

$$\ln(Y) = \alpha + \beta_1 \ln(X_1) + \beta_2 \ln(X_2) + ... + \beta_n \ln(X_n) \quad (1)$$

Y = Dependant variable

α = Constant

β = Coefficients

X = Independant variables

n = Number of independant variables

Independent variables in this model are socio-economic and land-use factors that correlate significantly with car ownership (Table 3.10) (see '2006\ log-linear model2006\car ownership log linear.spv' in Appendix 3). The log-linear relationship between dependent and independent variables shows that some of the log-linear coefficients are conflicting with the results of correlations. For example, while the proportion of household annual income is positively correlated with car ownership, the sign of the regression coefficient for the car-ownership model is negative (Table 8). This is because of the co-linearity among selected independent variables.

Table 8. Log-linear regression analysis for ln (car ownership) in Melbourne (2006)

Independent variables	**Standardised coefficients**	**p-value**	**Variance inflation factor**
Constant (-)	14.86	N/A	N/A
ln (household annual income) ($)	-0.03	0.50	1.06
ln (proportion of couples with children to other household types (-)	0.50	0.00	1.04
ln (population density) (person/ha)	0.11	0.02	1.10
ln (access to public transport) (km)	0.07	0.19	1.23
ln (proportion of detached houses to other dwelling types) (-)	0.24	0.00	1.08
ln (walkability) (-)	-0.08	0.17	1.35
Adjusted $R^2 = 0.34$			

Following the same process using a linear-regression model, stepwise regression was used to solve the co-linearity problem (Table 9).

Table 9. Stepwise log-linear regression for ln (car ownership) in Melbourne (2006)

Independent variables	**Standardised coefficients**	**p-value**	**Variance inflation factor**
Constant (-)	0.43	N/A	N/A
ln (proportion of couples with children to other households) (-)	0.51	0.00	1.00
ln (proportion of detached houses to other dwelling types) (-)	0.23	0.00	1.00
Adjusted $R^2 = 0.33$			

- ***VKT model***

The same approach was done for estimating VKT using a log-linear regression model and stepwise model. Ln (VKT) is represented as functions of significant land-use and socio-economic factors (Table 10, 11) (see '2006\ log-linear model2006\vkt log linear.spv' in Appendix 3):

Table 10. Log-linear regression analysis for ln (VKT) in Melbourne (2006)

Independent variables	**Standardised coefficients**	**p-value**	**Variance inflation factor**
Constant (km)	-21.37	N/A	N/A
ln (household annual income) ($)	0.023	0.59	1.07
ln (proportion of couples with children to other household types) (-)	0.03	0.54	1.45
ln (access to public transport) (km)	0.03	0.51	1.33
ln (distance from CBD) (km)	0.26	0.00	1.30
ln (walkability) (-)	0.02	0.65	1.55
ln (car ownership) (-)	0.60	0.00	1.47
ln (area of SLA) (km^2)	0.1	0.05	1.57
Adjusted R^2=0.51			

Table 11. Stepwise log-linear regression for ln (VKT) in Melbourne (2006)

Independent variables	**Standardised coefficients**	**p-value**	**Variance inflation factor**
Constant (km)	2.04	N/A	N/A
ln (car ownership) (-)	0.61	0.00	1.08
ln (distance from CBD) (km)	0.27	0.00	1.14
ln (area of SLA) (km^2)	0.10	0.03	1.23
Adjusted R^2=0.51			

- ***Modal split mode***

  Modelling percentage of car trips with a log-linear model leads to the following results (Table 12, 13) (see '2006\ log-linear model2006\modal log linear.spv' in Appendix 3).

Table 12. Log-linear regression analysis for ln (percentage of trips by car) in Melbourne (2006)

Independent variables	**Standardised coefficients**	**p-value**	**Variance inflation factor**
Constant (%)	-29.20	N/A	N/A
ln (household annual income) ($)	0.26	0.00	1.03
ln (proportion of couples with children to other household types) (-)	-0.14	0.03	1.42
ln (population density) (person/ha)	-0.08	0.18	1.38
ln (access to public transport) (km)	-0.03	0.61	1.24
ln (walkability) (-)	0.01	0.83	1.53
ln (car ownership) (-)	0.16	0.01	1.53
ln (area of SLA) (km^2)	0.20	0.00	1.80
Adjusted R^2=0.15			

Table 13. Stepwise log-linear regression for ln (percentage of trips by car) in Melbourne (2006)

Independent variables	**Standardised coefficients**	**p-value**	**Variance inflation factor**
Constant (%)	-28.55	N/A	N/A
ln (household annual income) ($)	0.26	0.00	1.03
ln (area of SLA) (km^2)	0.24	0.00	1.03
Adjusted R^2=0.14			

2.3. Neural network model

The neural network analysis was implemented for Melbourne data in Matlab, where car ownership, VKT and modal split were introduced to the model as outputs and selected socio-economic and land-use factors were introduced as inputs. 70% of data were used for training, 15% for validation and 15% for testing, which is the default setting in Matlab. Corresponding mean square error (MSE) and R^2 value for each model is provided in Table 14 (see 'CCD level\ NN 2006\car ownership R.jpg, car ownership NRMSE.xlsx, car ownership.m, VKT R.jpg, NRMSE VKT.xlsx,vkt.m, R modal. jpg, modal NRMSE.xlsx, modal.m' in Appendix 3). MSE is the average squared difference between observed and estimated variables, and R^2 measures the correlation between observed and estimated variables. Low MSE and high R^2 shows that neural network is capable of modelling transport behaviour as functions of socio-economic and land-use factors.

Table 14. MSE and R^2 values from neural network models

	MSE	R^2
Car ownership model	0.07	0.53
VKT model	0.10	0.60
Modal split model	0.01	0.51

2.4. SLAs and CCDs comparison

Comparison of different modelling techniques showed that in CCD level, ANN provides highest R^2 and lowest NRMSE, so it is the best modelling technique for land use/transport interaction modelling. This is the same for SLA level. To evaluate spatial transferability of land-use/transport interaction models, different modelling techniques were compared for SLA and CCD levels (Tables 15, 16, 17). The results confirmed that although ANN provides the best results for both SLA and CCD level, that appropriate technique for modelling land-use/transport relationship is site specific, and type of relationship (i.e. linear, and non-linear) between land-use factors and travel behaviour measurements changes based on selected spatial scale. For example, while log-linear regression provides better results (lower NRMSE and higher R^2) for modal split in SLA, log-linear regression is better for predicting car ownership in CCD level compared to SLA level. On the other hand, it was found that SLA level (larger spatial level) is better for VKT and modal split modelling, using ANN.

Table 15. Car ownership model at SLA and CCD level

	Car ownership in SLA	Car ownership in CCD
Linear regression analysis	R^2 =0.40, NRMSE= 26.83%	R^2 = 0.34, NRMSE= 21.05%
Log-linear regression analysis	R^2 =0.23, NRMSE= 95.26%	R^2 = 0.33, NRMSE= 30.55%
ANN	R^2 =0.66, NRMSE= 14.87%	R^2 =0.53, NRMSE= 12.26%

Table 16. VKT model at SLA and CCD level

	VKT in SLA	VKT in CCD
Linear regression analysis	R^2=0.44, NRMSE=22.56%	R^2=0.46, NRMSE=10.82%
Log-linear regression analysis	R^2 =0.45, NRMSE= 9.77%	R^2 =0.51,NRMSE= 12.25%
ANN	R^2 =0.75, NRMSE= 6.11%	R^2 =0.60, NRMSE= 8.94%

Table 17. Modal split model at SLA and CCD level

	Modal split in SLA	**Modal split in CCD**
Linear regression analysis	R^2=0.76, NRMSE=1.54%	R^2=0.18, NRMSE=15.51%
Log-linear regression analysis	R^2 =0.81, NRMSE= 2.12%	R^2=0.14, NRMSE=4.99%
ANN	R^2 =0.93, NRMSE= 0.97%	R^2 =0.51, NRMSE= 3.03%

Appendix 3. Thesis related data and analyses

A CD attached to this thesis contains data used and analyses undertaken. Location in the directories for each file is provided through the thesis, where reference is made.