# EXPLORING SOCIO-ECONOMIC TREND IN PRIVATE VEHICLE FUEL EFFICIENCY: A COMPARATIVE STUDY OF BRISBANE AND SYDNEY, AUSTRALIA

*Tiebei Li, Jago Dodson and Neil Sipe*

*Griffith University, Brisbane 4111, QLD, Australia. Email: t.li@griffith.edu.au*

## ABSTRACT

Australian cities have seen continued growth in private car travel that has imposed increasing vehicle energy consumption and greenhouse gas emissions. While much research has shown that travel demand is related to urban spatial structure, very little research has investigated the association of vehicle fleet fuel efficiency (VFE) and socio-economic circumstance in urban areas. In this paper, we apply a Geographically Weighted Regression to explore intra-urban trends in socio-economic adoption of high efficient private vehicle using the case studies of Brisbane and Sydney, Australia. Specific attention is given to 1) what are the areas associated with high and low levels of VFE; and 2) how the VFE is associated with socio-economic variables (for example, household income) at local area. The identified spatial associations are then compared between Brisbane and Sydney to examine some important differences in the types of factors that associated with VFE in both cities. We conclude by highlighting outcomes from this research that are of relevant to policy makers, including those charged with identifying high oil vulnerable communities, designing intervention strategies such as implementing social and financial programs to improve household vehicle efficiency.

*Key words: vehicle fuel efficiency, socio-economic factors, geographically weighted regression*

# Introduction

Australia is the one of the most car dependent countries in the world. In 2010, there were 12.3 million private vehicles registered in Australia, representing an increase of 12.6% over 2005. (Australian Bureau of Statistics, 2010). The continued growth in car travel and traffic congestion has resulted in increasing levels of fuel consumption and greenhouse gas emissions in Australia. In addition, the increase in automobile dependence in Australian cities has placed them at greater risk from potential adverse social and economic outcomes arising from increasing petrol prices (Dodson and Sipe, 2008). Reducing fuel use and carbon emissions, especially for private vehicles, remain a key objective of Australian urban policy (Australian Government, 2010). Current Australian national strategies for managing vehicle energy consumption and carbon emissions focus on both managing private vehicle travel demand and incentives programs such as financial rebate and awareness campaigns in promoting energy efficient vehicles. In 2002, the national vehicle efficiency target was set with a goal of reducing average vehicle fuel consumption from 11.1 litres/100km to 8.2 litres/100km by 2010. Although the industry did not achieve the targets, there was still noticeable improvement in fuel economy (Australian Bureau of Statistics, 2010).

From a policy perspective, vehicle energy policy and regulation will have to be based on a good understanding of the characteristics of current Australian vehicle fleet and socio-economic potential for improving the private vehicle fuel efficiency. Previous research in this field found that household vehicle use, fuel efficiency and environmental performance is associated with household income and other socio-economic factors, and has drawn particular attention to the importance of socio-economic influences on energy and environmental efficiency of urban private vehicle fleet (Choo and Mokhtarian, 2004; Fang, 2008; Bhat et al., 2009; Brownstone and Golob, 2009). However, there has been very limited research that has explored spatial relationship between private vehicle fuel efficiency and socio-economic characteristics in Australian cities. Whilst previous research has shown that the vehicle fleet composition is related to urban social and spatial structure (Bhat, et al., 2007; 2009), there is very little research has investigated the relationship between vehicle fleet fuel efficiency (VFE) and socio-economic circumstance in urban areas. In this paper, we use the Australian 'Green Vehicle' Guide (provides the energy and environmental performance of passenger vehicles in Australia) combined with motor vehicle registration records to examine the association between VFE and socio-economic characteristics (based on the 2006 Australian Census). The primary aim of this paper is to explore intra-urban trends in socio-economic adoption of more fuel efficient vehicles using Brisbane and Sydney, Australia as case studies. The purpose of the comparison is to examine if there is any commonality in the types of factors that are associated with VFE in both cities. We have focused on three questions: 1) what areas are associated with high and low levels of VFE?; 2) how is VFE associated with socio-economic characteristics?; and 3) what differences exist between Sydney and Brisbane. In so-doing we aim to establish if the methodologies and findings are transferable across different geographical, environmental and social contexts.

In the absence of disaggregated data at the level of individual households, a spatial approach is adopted in order to conduct a preliminary analysis of the characteristics of areas associated with high and low level of VFE. A geographically weighted regression (GWR) (Fotheringham, et al., 2002) is adopted in a comparative context to examine how the VFE is associated with census variables at an intra-urban scale of analysis to identity the types of factors that may be influencing such trends. The reminding paper is structured as follows: the next section reviews the previous studies on VFE and social economic factors. Then section three and four outline study areas and data development. The section five and six detail the method, variables and model development. Then the modelling results are explained and discussed in the section seven and eight. In the last section, the paper concludes with a discussion of research outcomes and the limitation of the research and outline of avenue forward.

We conclude by comparing the trends between Sydney and Brisbane and by highlighting outcomes from this research that are of relevant to vehicle energy policies,

## Vehicle fleet efficiency and socio-economic factors

Attempts to understanding the nature of relationship between socio-economic distribution and urban vehicle fleet has been addressed by a variety of disciplines/policy areas including: consumer behaviour (Mccarthy and Tay, 1998, Bhat and Pulugurta, 1998, Choo and Mokhtarian, 2004); forecasting vehicle market (Mannering and Winston, 1985; Bunch et al., 1996); land use planning (Bhat and Guo, 2007; Fang, 2008); transport demand forecasting and planning (Train and Lohrer, 1982; Berkovec, 1985; Golob and Wissen, 1989; Golob et al, 1997); social inequity and oil vulnerability (Litman, 2005; Dodson and Sipe, 2007); and energy consumption and environmental sustainability (Feng et al., 2004).

Numerous studies have identified the importance of socio-economic impacts on vehicle choices. Manski and Sherman (1980) examined household vehicles and socio-economic composition. They report that the socio-economic factors including household size, income and number of workers were very influential in determining vehicle holdings. Hensher (1985) found that vehicle type was directly influenced by the number of vehicles and patterns of vehicle utilization within a household. Mannering and Winston (1985) demonstrated the importance of factors such as housing type/tenure and socio-economic status in explaining vehicle fleet patterns. Using a 1989 household survey of new vehicle buyers, Mccarthy and Tay (1998) explored household behaviour on new vehicle consumption and showed that consumers associated with lower socio-economic status had lower demand for fuel efficient vehicles. In a recent review of research on socio-economic association and vehicle holdings, Bhat et al. (2009) found that age, income, gender, household size and housing tenure were strongly correlated with the vehicle ownership and use.

In the recent years, there has been a particular focus on the examination of socio-economic characteristics and fuel efficient and environmentally friendly vehicle types. The household 'vehicle type', typically measured by body type or engine size is widely used as an indicator that is most relevant to analysing fuel consumption and efficiency (Bhat et al, 2009). In one study, Brownstong et al. (2000) employed a joint mixed logit model and found that the low fuel consumption vehicles (represented by large vehicle types) were more often associated with households having low incomes and/or low education levels. Bhat et al. (2009) and Eluru et al. (2010) explored the association between household vehicle type and socio-economic characteristics and found a strong association between residential density and public transport accessibility. Choo and Mokehtarian (2004) showed that in addition to socio-economic characteristics, some subjective factors (e.g. travel attitude, personality and lifestyle) significantly influence household vehicle choice. Using household travel survey data, Brownstong and Golob (2009) modelled the relationship between vehicle fuel consumption and a range of demographic variables in California using simultaneous equation models. The results demonstrated important exogenous influences from variables such as the number of drivers, the number of workers, household income and education on vehicle fuel consumption.

Dodson et al. (2009) used data for Brisbane private vehicle fleet to compare the socio-economic status of urban residents with the age and engine size of the vehicle fleet. The research demonstrated a correlation between vehicle energy use and socio-economic disadvantage, with outer urban disadvantaged groups found to be more frequent users of old and large engine vehicles and thus exposed to higher fuel costs. The socio-economic pattern of vehicle fuel consumption was further investigated by Li et al. (2011) who provided an exploratory analysis of vehicle energy consumption based on a spatial analysis of vehicle travel distance and the efficiency composition of the vehicle fleet in Brisbane, Australia. The results showed the average VFE decreases as the household's travel demand increases. This finding demonstrates that the vehicle fleet composition is influenced by household travel demand which in turn compounds disadvantage and vulnerability.

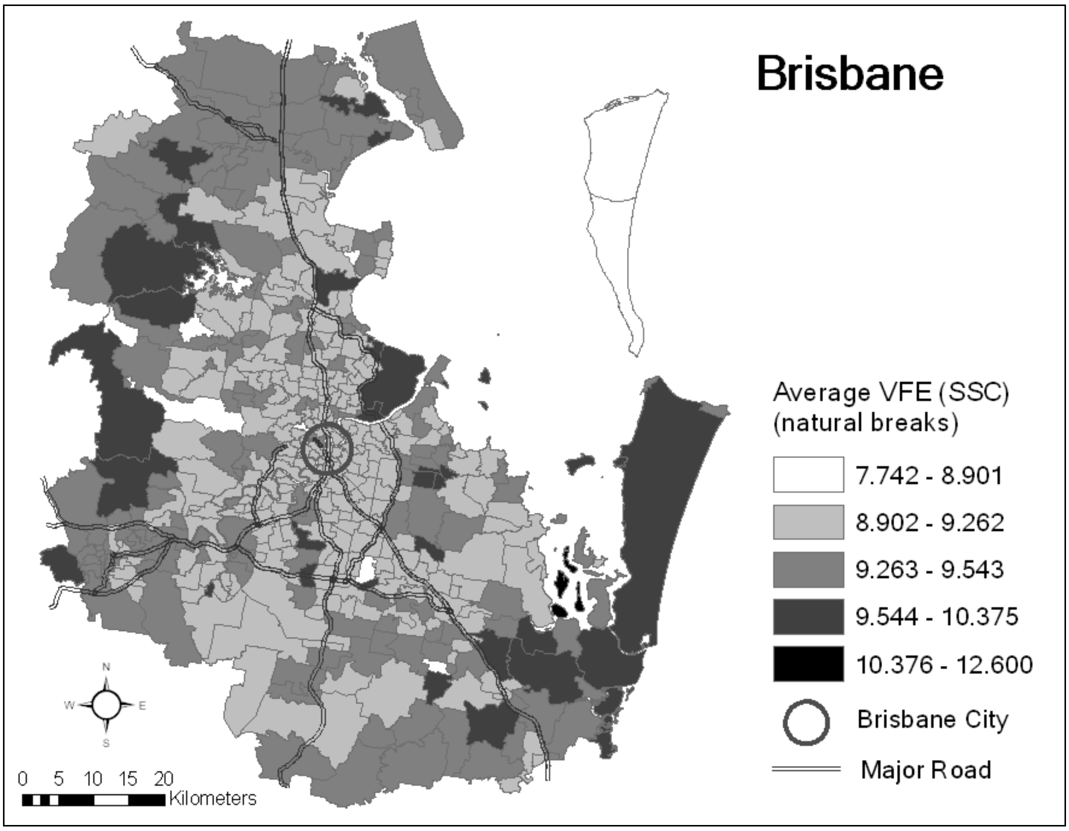
The existing body of research has revealed interesting levels of association with socio-economic variables and vehicle fleet efficiency. However, exploring socio-economic patterns and trends in VFE remains a challenge with increasing complexity in vehicle fuel technology, fleet composition, and household vehicle choices. While much research has shown that household vehicle type (often measured by vehicle body type or engine size) is associated with socio-economic structure, there is relatively little research that has explored the direct association of actual energy performance of private vehicle fleet (e.g. litres of fuel per 100km) and socio-economic circumstance in urban areas. Examination of social-vehicle efficiency relationship in urban areas will have direct implications for household transport energy patterns and successful energy policy options. The limitations of the use of vehicle type for household vehicle energy analysis are: 1) it may not provide an accurate measure of fuel efficiency of the vehicles (e.g. many large body vehicles are fuel efficient); 2) it forces the dependent variable, VFE, to be categorically discrete (e.g. using broad vehicle type classifications) which will mask important underlying spatial associations in urban areas. This paper addresses the gap through an analysis of socio-economic structure and the efficiency composition of the private vehicle fleet by linking the vehicle fleet to standard vehicle fuel efficiency ratings at an individual vehicle level. This provides a rich depiction of VFE distribution, not only of the car ownership and vehicle types, but also of the relative levels of fuel consumption of the vehicle fleet.

Most of the previous studies have examined spatial patterns of vehicle energy efficiency and socio-economic factors for a single city. This limits the transferability of many of the findings. It is possible that the underlying trends in VFE in relative to socio-economic factors may not be consistent across urban areas with different contextual situations. Thus, further research should be carried out to examine how the findings compare across urban areas having different social, demographic, geographic and environmental contexts. In this paper we aim to extend the analysis to an intra-urban comparison of VFE trends for two cities – Brisbane and Sydney, to examine if there is any commonality in the types of factors that are associated with VFE in both cities, drawing on comparable sources of vehicle fuel efficiency and census data.

## Vehicle fuel efficiency (VFE)

In this study, the spatial distribution of fuel efficiency of private vehicles was modelled through a combination of private motor vehicle registration data and the Australian Government's 'Green Vehicle' fuel efficiency data. The private motor vehicle registration data was obtained for 2008 and includes 520,576 private motor vehicle records for Brisbane and 700,261 for Sydney. Each record contains the make, model, year, body type, number of cylinders, and suburb location (state suburbs, SSCs). The Australian Government 'Green Vehicle' guide provides information on the environmental performance for 14,996 vehicle makes and models that were sold in Australia between 1986 and 2003, and manufactured in 2005 and 2009. The guide includes information on air pollution, CO2 emissions, noise, and fuel consumption by vehicle make/model. For this study, the fuel consumption rate (litres/100km) was extracted and used for the VFE analysis as it provides accurate information on standard fuel consumption for each vehicle make and model. Fuel consumption rates by make and model were allocated to each individual vehicle in the vehicle registration database. Details of this procedure is explained in our previous research (Li, et al 2011). Once the fuel efficiency information was allocated, all vehicle registration records containing a VFE value were then aggregated at the suburb level and the average VFE was calculated based on the total number of private vehicles.

The distribution of average VFE (measured by litres/100km) for Brisbane and Sydney is shown in Figure 1. A high VFE means low fuel efficiency and a low VFE means high fuel efficiency. Overall, the spatial variation in the average VFE between suburbs is relatively small. This is because: 1) the range of VEF variation in most vehicles is small (e.g. the standard VFE for most vehicles ranges from 9 to 11 litre/100km); and 2) many suburbs have a mix of high and low VFE vehicles which dilutes the spatial variation in VFE. However, some spatial patterns can be observed in both cities. In both Brisbane and Sydney, the average VFE tends to be lower in inner urban areas surrounding the city centre. These areas are surrounded by suburbs with average energy efficiencies. In contrast, suburbs to far west and far southeast in Brisbane, and the far north Sydney, exhibit the lowest vehicle efficiencies. Although VFE tends to be higher with increasing distance from the city centre, some local variations exist. This can be caused by the higher proportion of large/high performance vehicles (e.g. SUVs) used in some high income suburbs that reduced overall energy efficiency. The lower vehicle efficiency observed in some blue collar suburbs suggests that occupation may affect their vehicle choice (e.g. a higher proportion of mini-vans and light trucks).



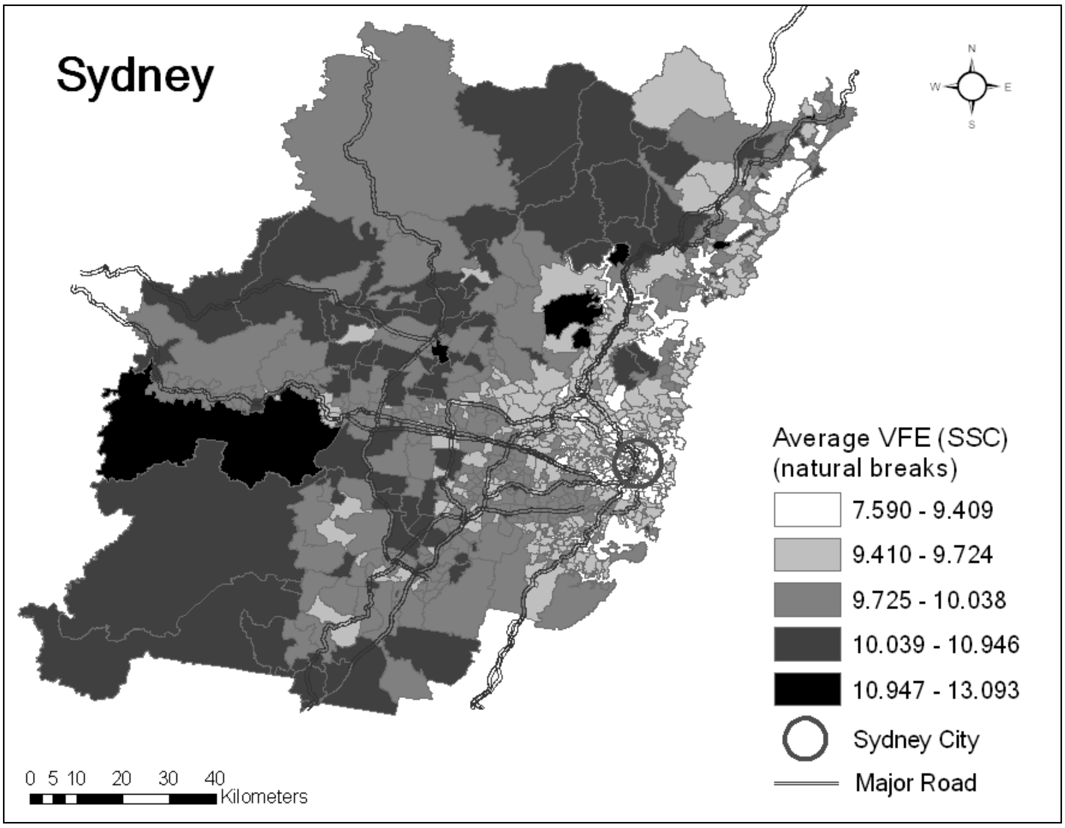



Figure 1 - Distribution of average VFE (litre/100km) in Brisbane and Sydney

## Census data

The Australian Bureau of Statistics (ABS) provides census data for state suburbs (SSCs). We used the ABS statistical division (SD) as the boundaries for Brisbane and Sydney. The census variables at the suburb level were used to ensure that the spatial units matched the spatial boundary of the motor vehicle registration data. Therefore, the relationship between socio-economic characteristics of resident population and VFE can be examined at the suburb level for both Brisbane and Sydney.

Table 1 provides a comparison of Brisbane and Sydney. In general, Sydney's population is more than twice as large as Brisbane's. Although the Sydney statistical division covers a larger geographical area (over four times that of Brisbane), the dwelling unit density in Sydney is considerably higher than Brisbane's. The compact development in Sydney is also reflected by a higher proportion of compact dwellings (units and townhouse dwellings) and its overall road density. People living in Brisbane tend to be more car dependent than Sydney residents. This is demonstrated by the significantly higher proportion of multi-vehicle dwellings and the higher percentage of car-based travel in Brisbane. The average vehicle fuel efficiency in Brisbane is slightly lower than Sydney's fleet as derived from the motor vehicle data. In addition, by comparing some economic variables (e.g. household mortgage and household weekly rent), households in Sydney have higher incomes but pay higher mortgages and rent. Overall, Brisbane and Sydney are very distinct areas, each with different social, economic and spatial characteristics. They provide an ideal context in which a broad pattern of social-transport VFE associations can be more rigorously evaluated and compared.

Table 1 - Comparison of Brisbane and Sydney

| **Variables** | **Brisbane** | **Sydney** |
|---|---|---|
| Population (million) | 1.82 | 4.10 |
| Area (1000km$^2$) | 5.13 | 21.23 |
| Number of suburbs | 440 | 810 |
| Number of private vehicles (1000) | 520.5 | 799.2 |
| Average vehicle fuel efficiency (litres/100km) | 9.27 | 9.13 |
| Total number of dwellings (1000) | 647.2 | 1,417.6 |
| Mean household weekly income ($) | 1,151 | 1,271 |
| Road density (km/km$^2$) | 8.7 | 20.1 |
| Mean weekly rent ($) | 220 | 260 |
| Mean monthly home mortgage ($) | 1,340 | 1,850 |
| Mean household size (persons) | 2.65 | 2.74 |
| Total number of new migrants in the past 5 years (1000) | 84.2 | 23.3 |
| Proportion of flat and unit dwellings (%) | 12.5 | 23.1 |
| Dwelling density (dwellings/ /km$^2$) | 392 | 735 |
| Proportion of journey to wok trips using private vehicles (%) | 84.6 | 60.7 |
| Proportion of population with a bachelor degree or above (%) | 12.2 | 14.7 |
| Median age | 35.2 | 36.9 |
| Proportion of dwellings with more than one vehicle (%) | 56 | 51 |

# GWR

The analyses of trends in socio-economic adoption of VFE have formed the basis for a number of studies (for example, Brownstong et al. 2000, Brownstong and Golob 2009). There is relatively little research that has explored the potential associations of census data and VFE at the intra-urban scale. Spatial-based techniques can be used to analyse the motor vehicle data, including some advanced statistical analyses designed to explore spatial trends. In order to identify local relationships between VFE and socio-economic characteristics at an intra-urban scale, a GWR model is applied in a comparative context to examine intra-urban trends in socio-economic adoption of high efficient vehicle.

The spatial methodology identifies the socio-economic determinants of VFE by modelling the relationships using GWR (Fotheringham, et al., 2002). GWR is a multivariate regression technique that estimates relationships at a local level using the weighted data samples based on their spatial proximity, accounting for local variations in ecological relationships. The more traditional global Ordinary Least Squares (OLS) regression approaches are unable to capture this phenomena. It produces a separate set of regression parameters for every location of analysis (e.g. a SSC) across the study area. Therefore, it relaxes the assumption in the traditional OLS models that the relationships (regression coefficients) between the dependant and the independent variables being modelled are constant across a study area. The specific GWR model is specified as:

$$Y(i) = ß_0(i) + ß_1(i)\ Xn + \varepsilon \qquad (1)$$

where: Y is the dependent variable; $X_n$ is the independent variable; $ß_0$ and $ß_1$ are the parameters to be estimated and $\varepsilon$ is a random error term, assumed to be normally distributed; *i* represents the vector of co-ordinates of the location, which indicate that there is a separate set of parameters for each of the g observations. When using GWR the coefficient can be estimated by solving:

$$ß(i) = (X^T W(i) X)^{-1} X^T W(i) Y \quad (2)$$

where W(*i*) is the weight matrix denoting the connectivity between the observations. The weight can be determined by the Gaussian function. The weight for the observation *i* is shown in Equation 3:

$$W(i) = \exp(-d/h)2 \quad (3)$$

where *d* is the Euclidean distance between the location of observation *i* and the location of analysis and *h* is a quantity known as the bandwidth of the sampled observations. The bandwidth may be defined either by a given distance or a fixed number of nearest neighbours from the analysis location. The optimal number of the nearest neighbours is determined by minimising the Cross Validation score (CV) or through selecting the model with the lowest Akaike Information Criterion (AIC) score (Hurvich et al., 1998), given as:

$$AIC_c = 2n\log_e(\hat{\sigma}) + n\log_e(2\pi) + n\left\{\frac{n+tr(S)}{n-2-tr(S)}\right\} \quad (4)$$

where *tr(S)* is the trace of the hat matrix. The *AIC* method has the advantage of being more general in application than the CV statistics and it can be used to select between a number of competing models by taking into account the differences in the model complexity (Fotheringham et al., 2002).

There is some limited evidence of the application of the GWR technique in urban transport where the approach was found to be of greater utility in its superior ability to capture local social processes of household VKT and household car dependency (Mulley and Tanner, 2009; Paez and Currie, 2010). In addition, GWR was found to offer a method by which the misspecification of global models could be examined (Cahill and Mulligan, 2007). In a study of public transport investment in the San Francisco (California)area, Paez (2006) concluded that global regression approaches demonstrated an inability to capture local variations in ecological relationships and as a result this reduced their overall explanatory power. In a study of public transport accessibility in Riga (Latvia), Dmitry (2009) identified the value of GWR was in its capacity to better guide housing price policies through more specific spatial neighbourhood targeting.

To compute the GWR models, an ArcGIS extension is employed using the data for Sydney and Brisbane. Four models (two GWR models and two OLS models) are estimated and compared for Brisbane and Sydney. Each model uses the average VFE across suburbs as the dependent variable and the socio-economic variables as the explanatory variables. To determine the best subset of the explanatory variables, the Akaike Information Criterion (AIC) procedure was used (Akaike 1981). The GWR models are statistically compared to a global OLS model for evaluation purposes using the F-test and AIC values of both models.

# Model selection

It should be noted that there is a mismatch between use of 2008 private vehicle registrations and the 2006 Census data. However we assume there is no major vehicle fleet change between 2006 and 2008 for the study area. In this study, 13 independent variables were selected (see Table 1) based on the literature review. These variables include age, ethnicity, family composition, qualification, income, housing tenure, housing types and living stability.

We eliminated other factors that were highly correlated to the independent variable to reduce the effect of multicollinearity.

OLS and GWR models were developed using the average VFE for each suburb (dependent variable) and the 13 socio-economic factors as the independent variables. Separate models for Brisbane and Sydney were computed. From the starting list of independent variables a process of statistical elimination resulted in total seven independent variables being selected to remain in the final models. These include household size (*Size*), household weekly income (*Income*), household weekly rent (*Rent*), qualification (*Education*), housing tenure (*Owned*), housing types (*FlatU*) and local road density (*Road*). The definition of each of these variables was provided in Table 2.

The GWR models were formulated as:

*Brisbane model:*

$$\text{VFE}(i) = \text{ß}0(i) + \text{ß}1(i)\text{Income} + \text{ß}2(i)\text{Rent} + \text{ß}3(i)\text{Owned} + \text{ß}4(i)\text{FlatU} + \text{ß}5(i)\text{Road} + \varepsilon(i), \quad (5)$$

*Sydney model:*

$$\text{VFE}(i) = \text{ß}0(i) + \text{ß}1(i)\text{Income} + \text{ß}2(i)\text{Rent} + \text{ß}3(i)\text{Education} + \text{ß}4(i)\text{Size} + \text{ß}5(i)\text{Road} + \varepsilon(i), \quad (6)$$

Only significant variables are contained in each GWR model. VFE is the average private vehicle fuel efficiency in a suburb; *i* denotes the *i* th suburb location in the study region; $ß_n$ is the coefficient for the variable *n*; $ß_0(i)$is the local intercept at location *i*; and ε*(i)* is the error term remained at suburb location *i*.

GWR is used to analyse the local relationships (coefficients) between average VFE and each independent variables at the local level. Here, an adaptive kernel is used for the local regression to account for the irregular distance between the data observations (defined as the number of the nearest neighbours that is determined by minimizing the AIC score of the model). The data within the kernel are weighted by their distance from the regression point (a suburb centroid). Hence, the data points closer to the regression point are weighted more heavily in the local regression with the weights decreasing with the distance from this location following a Gaussian decay function. Thus, each individual suburb location (as a regression point) has a set of relationships defined in the local regression so that the resulting coefficient estimates vary across the study region.

## Modelling results

A statistical summary of coefficients estimated by the OLS and GWR models is provided in Table 2. Overall, the variables in the Sydney models perform slightly better than those in the Brisbane models in explaining the variation in VFE. This is evidenced by the higher *t* value of coefficient estimated for each variable reported by the Sydney models. Several important observations can be made about these modelling efforts. First, some previously identified variables that were significant for vehicle type variables (e.g., vehicle body type or engine size) do not appear to be significant factors in explaining VFE. This is particularly the case for the variables *age*, *employment* and *vehicle ownership* and *ethnicity* variables that were not found to be correlated with VFE distributions in either city. Second, variables *rent*, *income* and *road density* were the three variables that are significant for explaining the VFEs for both Brisbane and Sydney. This suggests that built environment and economic status tend to be more transferable factors related to VFE across different urban contexts. Third, some variables show strong relationships to VFE in one city, but not significant in the other. The variables *household size* and *education* tend to be more important factors for Sydney, but are not significant in Brisbane. On the other hand, variables for *house tenure* (owned) and *dwelling type* (FlatU) have significant relationship in Brisbane, but are not significant in Sydney.

Table 2 - Explanatory variables for Brisbane and Sydney models

| **Independent variable (suburb)** | **Model**<br>**OLS**<br>*Brisbane*<br>Coefficient (*t*) | <br>**OLS**<br>*Sydney*<br>Coefficient (*t*) | <br>**GWR**<br>*Brisbane*<br>Min : Max<br>Mean | <br>**GWR**<br>*Sydney*<br>Min : Max<br>Mean |
|---|---|---|---|---|
| Mean household size (**Size**) | - | 0.209 (*8.11*) | - | 0.081 : 0.330<br>0.246 |
| Mean weekly household income (**Income**) | -0.000069 (*-1.97*) | -0.00018 (*-4.38*) | -0.00035 : 0.00024<br>-0.00009 | -0.00026 : -0.00009<br>-0.00018 |
| Mean weekly household rent (**Rent**) | -0.0011 (*-4.92*) | -0.00019 (*-2.01*) | -0.0027 : 0.0004<br>-0.000686 | -0.00070 : 0.00039<br>-0.00011 |
| Proportion of people who achieved a qualification above high school (**Education**) | - | -0.0566 (*-6.77*) | - | -0.075 : -0.019<br>-0.0415 |
| Proportion of dwellings that are owned or being purchased (**Owned**) | -0.0188 (*2.74*) | - | -0.168 : 0.130<br>-0.0181 | - |
| Proportion of flat and townhouse dwellings (**FlatU**) | -0.0122 (*-1.67*) | - | -0.0520 : 0.0596<br>-0.0121 | - |
| Local road density (**Road**) | -0.00045 (*-1.83*) | -0.00162 (*-4.49*) | -0.0017 : 0.0001<br>-0.00048 | -0.0039 : 0.0001<br>-0.0012 |

('-' denotes not significant)

## Interpretation of spatial variation in local relationships

As shown in Table 2, the coefficients of independent variables vary greatly across each study region (showed by the lowest value and the highest value in the GWR models), and some individual variables show both negative and positive relationships to the dependent variable (VFE). These relationships are also depicted in Figures 4 (a–e) and 5 (a–e) in which the spatial distribution of the estimated relationships between VFE and the independent variables (coefficients) is illustrated. Each figure demonstrates that the independent variable exhibits a spatially-varied relationship to the VFE in Brisbane as well as in Sydney. The inset maps within Figures 4 and 5 show the significance of the estimated relationships between VFE and the independent variables (*t* values for coefficients derived from GWR models).

The variable *household income* (Income) shows a negative effect on VFE in Sydney, suggesting that Sydney households with higher incomes are likely to have more efficient vehicles. Figure 5a reveals that such this negative relationship tends to be stronger along coastal areas, then drops off dramatically at a north-south peri-urban belt and then the relationship remains moderate in the west. The negative relationship between household income and VFE were observed for most northern and southern suburbs in Brisbane (Figure 4a). Some positive relationships occur in Brisbane's inner south suburbs meaning that households with higher incomes own inefficient vehicles

The *household size* (Size) factor exhibits positive relationships to VFE only for Sydney only. This partly confirms the findings from previous research (e.g., Bhat et al., 2009) that a preference for bigger vehicles is associated with large households because they have more people to transport). Figure 5(c) illustrates that if a household has greater number of individuals, the dependency on inefficient vehicles tends to be higher and the level of dependency increases when they live close to the CBD. This may be due to higher activity engagement and travel demand for individuals in a large household in the urban areas.

Although the *level of education* (Education) is not a major determinant factor in Brisbane, it shows a clear negative impact on VFE distribution in Sydney. Figure 5d shows that the highest negative impacts are identified in north-east Sydney including higher socio-economic status areas such as Gosford and Central Coast. In these areas, people with a territory qualification have a higher preference for fuel efficient vehicles. The negative relationship tends to be weaker for people in Sydney's south-west. Overall, the Sydney result confirmed that people with higher education levels tend to prefer more efficient vehicles (Paleti et al, 2010).

The variable *weekly rent* (Rent) has an overall limited effect on VFE in both cities. Figure 4b illustrates that in the north-west and southern suburbs of Brisbane, an increase in household weekly rent results in a positive effect on local VFE (more efficient vehicles). However, the effect of weekly rent was not significant for a great number of suburbs in Brisbane. The negative relationship between these two variables was observed in the north and peri-urban western areas of Sydney (Figure 5b). The relationship was not found to be significant in the inner urban areas, reflecting more complex vehicle preferences for these households regardless of weekly rent.

Figure 4e shows that variable *house tenure* (Owned) tends to be negatively related to the VFE in south-east Brisbane, suggesting that residents who own or are buying their home are more likely to have inefficient vehicles. However, the relationship between house tenure and VEF were not significant for most other suburbs. The house tenure variable did not show any explanatory relationship to Sydney VFE at either a local or global level.

Another important determinant for Brisbane VFE is *dwelling types* (FlatU) measured by the proportion of flats, units and townhouses in a suburb. The variable is negatively associated with VFE for most suburbs, meaning that people living in more compact dwellings are less likely to have a highly efficient vehicle. However, this does not include the suburbs in south east Brisbane where the relationship between dwelling types and VFE is positive (see Figure 4c). The possible reason for this is that high density dwellings in the Redland Bay are waterfront apartments and people occupying these units tend to be wealthier and prefer inefficient vehicles (e.g., SUVs).

*Road density* (Road) is an important explanatory factor showing negative relationships in both Brisbane and Sydney. We argue that this is due to the fact that the suburbs with dense residential areas and road networks have space constraints for parking and operating of large and inefficient vehicles. The relationship in Brisbane shows local variation, with road density more important in some areas and less important for the inner west areas and some suburbs in south Brisbane. However, both Figure 4d and Figure 5e show that road density is less important to VFE in the inner urban areas.

In summary, although previous studies have demonstrated strong links between socio-economic variables and vehicle fleet types, we have not found this to be the case in our research. When using a standard measure of current vehicle fleet efficiency (litres/100km by make and model of the vehicles), we found that: 1) the VFE does not show a strong relationship to socio-economic factors; and 2) the VFE - socio-economic status relationship can vary greatly across study areas. The relationships for high density urban areas are weaker than those in outer suburbs in both urban areas. Estimated coefficients for a large number of suburbs did not have significant *t* values, although the Sydney models do slightly better. This is particularly the case for Brisbane's inner urban suburbs where the VFE pattern is more complex and difficult to be explained by the local socio-economic factors.

Finally, the results of the analysis of variance (ANOVA) in which the OLS model is compared with the GWR model is provided in Table 3. The results show that by accounting for the spatial non-stationary relationships the GWR models offers an improved goodness-of-fit (when compared to the OLS model) for both Brisbane and Sydney VFEs. The GWR model for Sydney presents a better goodness-of-fit than the GWR model for Brisbane (measured by both *r* squared and *AIC* statistics). In addition, the Moran's *I* statistics for residuals from each OLS and GWR model were calculated. The residuals form the OLS models show a moderate degree of positive spatial autocorrelation. In contrast, the Moran's *I* value of GWR models demonstrate that the residuals of GWR do not exhibit strong spatial autocorrelation. The GWR models in which spatially varied relationships are incorporated into the modelling process have largely controlled the problem of spatially autocorrelated error terms (Moran's *I*: Brisbane model = -0.012 and Sydney model = -0.014). This is not the case for both of the OLS models in which positive spatial autocorrelation remains in the residuals (Moran's *I*: Brisbane model = 0.223 and Sydney model = 0.241).

Table 3 - AVONA results for the OLS and GWR models.

| | **Brisbane** | | **Sydney** | |
|---|---|---|---|---|
| **Summary of statistics** | **OLS** | **GWR** | **OLS** | **GWR** |
| No. of Observations (SS) | 441 | 441 | 810 | 810 |
| No. of independent variables | 5 | 5 | 5 | 5 |
| No. of nearest neighbours (bandwidth) | - | 128 | - | 463 |
| AIC | - | -129.71 | - | 413.42 |
| r squared | 0.33 | 0.47 | 0.35 | 0.51 |
| Spatial autocorrelation of residuals (Moran's *I*) | 0.223 | -0.012 | 0.241 | -0.014 |

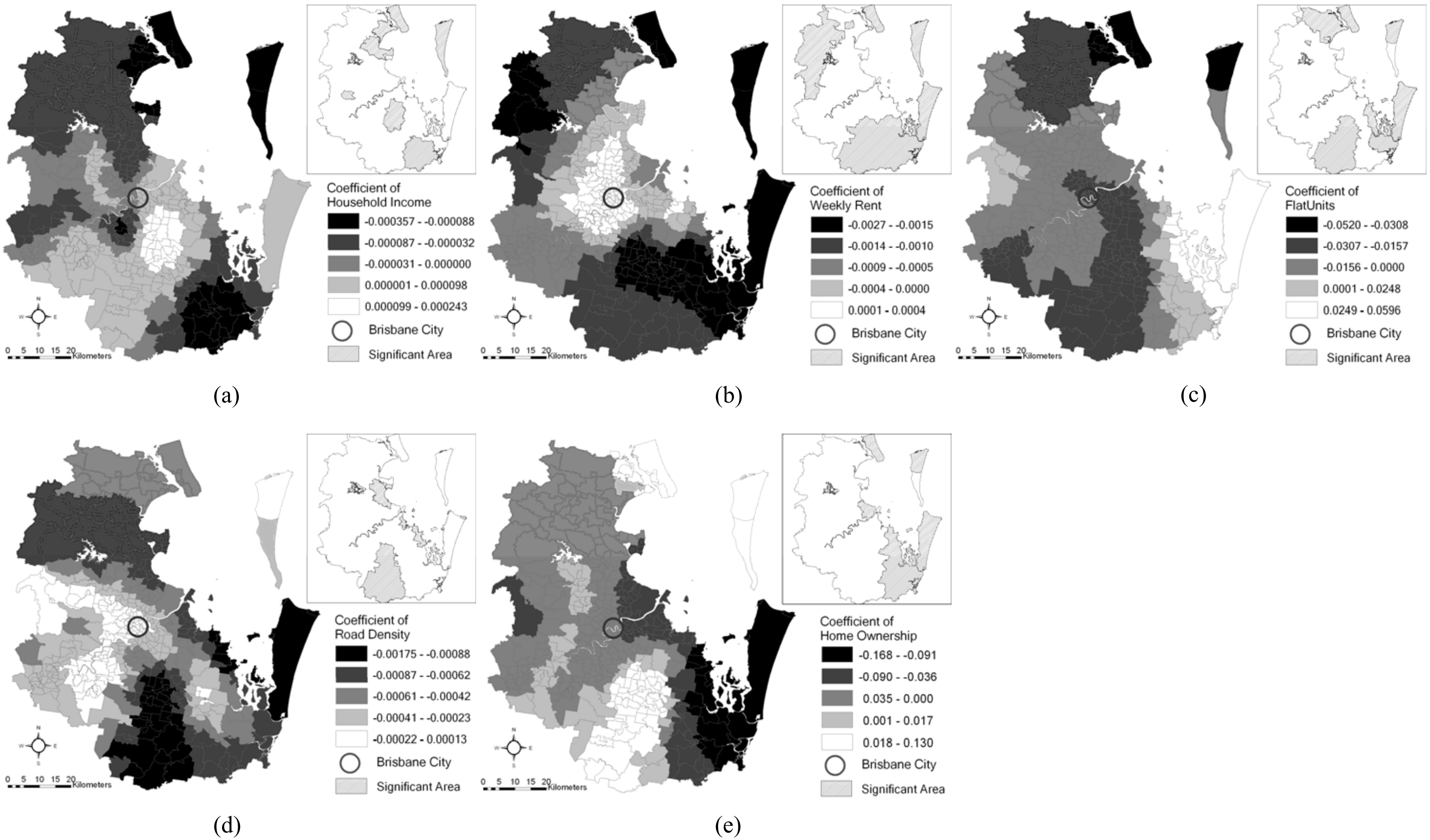



Figure 4(a) - (e) - Spatial variation of coefficients for Brisbane (each inset map displays the coverage of significant areas)

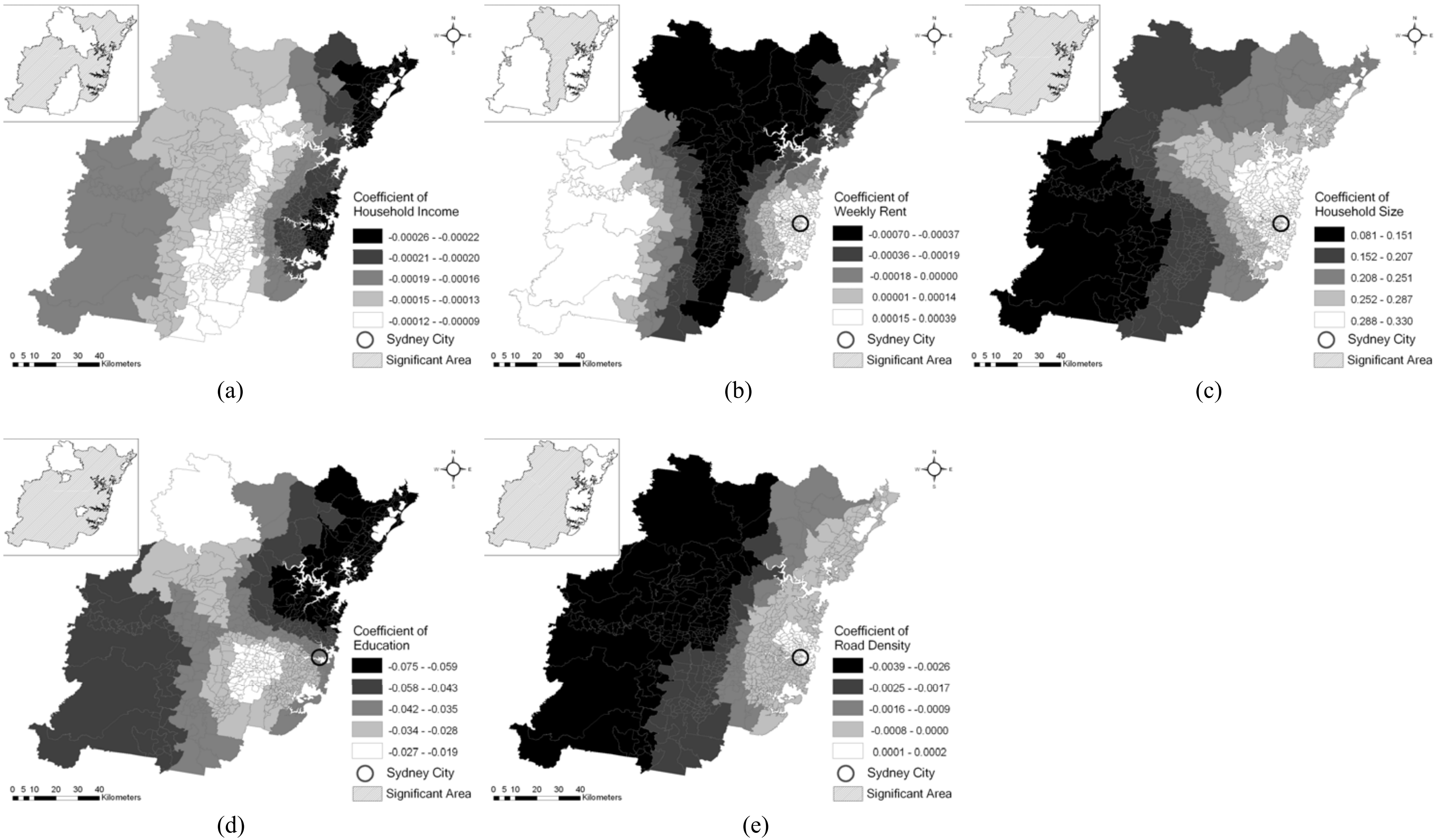



Figure 5 (a) - (e) - Spatial variation of coefficients for Sydney (each inset map displays the coverage of significant areas)

## Discussion and Conclusions

In this study we explored the association of VFE and socio-economic factors in two urban areas using spatial and statistical techniques. A review of literature has drawn attention to the association between demographic characteristics, population density, dwelling type, road development, etc. and their relationship on urban vehicle efficiency. This study integrates multiple, large data sources including motor vehicle registration data and Australian 'Green Vehicle' data along with socio-economic variables from Australian Census. The combination of standard VFE measures (litre/100km) and the entire private vehicle fleets permits more rigorous measures of VFE composition to better identify the nature of VFE according to socio-economic factors. In addition, a novel GWR technique was demonstrated which is capable of capturing changes in spatial variation in urban social-vehicle efficiency behaviour.

Through a spatial analysis of the VFE associated with the types of social-economic factors, the results show that in both Brisbane and Sydney there are a higher number of outer suburbs with low VFE than that in middle and inner suburbs. In general, the VFE (measured by standard vehicle fuel cost per 100km) does not show a strong relationship to socio-economic factors. This finding is at odds with previous studies that found strong links between socio-economic variables and vehicle types. Several variables that were significant in previous studies such as age, employment and vehicle ownership and ethnicity for explaining actual VFE were not significant in our research. This is particularly true for Brisbane, reflecting that VFE (and therefore energy and emission performance) is more complex than just vehicle type composition and is hard to explain from local socio-economic conditions. In addition, the results show that the relationships between VFE and socio-economic factors vary greatly across the study areas and that some variables have both positive and negative relationships to VFE. The possible reasons for such spatial variations and trends were suggested based on the respective spatial and socio-economic patterns of Brisbane and Sydney.

We acknowledge that the overall results can be partly related to data limitations. For example, many suburbs are relatively large which have a mix of both high and low VFE vehicles. Thus the average VFE will dilute the spatial variations between suburbs. In addition, the temporally consistent datasets (motor vehicle data and census data) should be used to investigate the spatial relationship between socio-economic variables and fuel efficiency across urban areas.

Whilst drawing attention to the types of socio-economic factors, this research has revealed detailed intra-urban trends in VFE in related to the socio-economic geography of both Brisbane and Sydney. This, in turn, has revealed some important similarities and differences in spatial associations in relation to social and spatial patterns of the two cities. The factors that relate to the household weekly rent, income and road development were found to be significant for explaining the VFE for both Brisbane and Sydney fleets. This means that built environment and economic status tend to be more transferable factors which relate to the VFE across different urban contexts. Through the comparative analysis has been made, there are some important contrast in the socio-economic associations with VFE for the two cities. Some variables have shown strong relationships to the VFE in one city, whereas their relationships for VFE are not significant in another.

This research has shown spatial nature of VFE and its relationship to a range of socio-economic factors. Both the results and methodology should have benefit for policy makers charged with identifying oil vulnerable communities and designing intervention strategies to improve household vehicle efficiency. Whilst it is difficult to establish the root cause due to the complexity of the data, the types of analysis reported in this paper have the potential to contribute the national targets for improving vehicle efficiency. Visualising these local relationships should also be of use to strategic planners to help develop appropriate energy mitigation policies and programs to spatially targeted areas. Finally, this comparative study has revealed variations in the types of factors associated with VFE in the two cities and identified important differences. Understanding the variations in the socio-economic determinants of VFE can improve policies for influencing household vehicle ownership and VFE in a way that reduces impacts on energy consumption and the environment.

## Reference

Australian Bureau of Statistics. (2010). Survey of motor vehicle use (cat. no. 9208.0). Canberra.

Australian Government. (2010). Our Cities - The challenge of change. Background and Research Paper. Canberra.

Australian Government. (2009). Information on green vehicle guide ratings and measurements. http:www.greenvehicleguide.gov.au/gvgblicui/Statccontent/ratings.aspx. Australian Government.

Berkovec, J. (1985). Forecasting automobile demand using disaggregate choice models. Transport Research Part B, 19(4), 315-329.

Bhat, C. R. and Guo, J. Y. (2007). A comprehensive analysis of built environment characteristics on household residential choice and auto ownership levels. Transportation Research Part B, 41(5), 506–526.

Bhat, C. R. and Pulugurta, V. (1998). A comparison of two alternative behavioral choice mechanisms for household auto ownership decisions. Transportation Research Part B, 32(1), 61-75.

Bhat, C. R. Sen, S. and Eluru, N. (2009). The impact of demographic, built environment attributes, vehicle characteristics and gasoline prices on household vehicle holdings and use. Transport Research Part B, 43(1), 1-18.

Brownstone, D. and Golob, T. F. (2009). The impact of residential density on vehicle usage and energy consumption. Journal of Urban Economics, 65(1), 91-98.

Brownstone, D. Bunch, D. S. and Train, K. (2000). Joint mixed logit models of stated and revealed preferences for alternative-fuel vehicles. Transportation Research part B, 34, 315-338.

Bunch, D. S. Brownstone, D. and Golob, T. F. (1996). A dynamic forecasting system for vehicle markets with clean-fuel vehicles. World Transport Research, 1, 189-203.

Choo, S. and Mokhtarian, P. L. (2004). What type of vehicle do people drive? The role of attitude and lifestyle in influencing vehicle type choice. Transportation Research A, 38(3), 201-222.

Dmitry, P. (2009). Statistical Analysis of the Relationship between Public Transport Accessibility and Flat Prices in Riga. Transport and Telecommunication, 10(2), 26-32.

Dodson, J. and Sipe, N. (2008). Shocking the suburbs: urban location, homeownership and oil vulnerability in the Australian city. Housing Studies 23(3), 377-401.

Dodson, J. Li, T. and Sipe, N. (2010). Urban structure and socio-economic barriers to consumer adoption of energy efficient automobile technology in a dispersed city: a case study of Brisbane, Australia. Journal of Transportation Research Board, 2151(2), 111-118.

Eluru, N. Bhat, R. Pendyala, R. M. and Konduri, K. C. (2010). A joint flexible econometric model system of household residential location and vehicle fleet composition/usage choices. Transportation, 37, 603-626.

Fang, H. (2008). A discrete-continuous model of household's vehicle choice and usage, with an application to the effect of residential density. Transportation Research part B, 42,736-758.

Feng, Y. Fullerton, D. and Gan, L. (2004). Vehicle choices, miles driven, and pollution policies. Department of Economics, The University of Texas at Austin.

Fotheringham, A. S. Brunsdon, C. and Charlton, M. (2002). Geographically Weighted Regression: The analysis of spatially varying relationships. John Wiley & Sons, Chichester.

Golob, T. F. Wissen, L. V. (1989) A joint household travel distance generation and car ownership model. Transportation Research Part B, 23 (6), 471-491.

Golob, T. F. Bunch, D. S. and Brownstone, D. (1997). A vehicle use forecasting model based on revealed and stated vehicle type choice and utilization data. Journal of Transport Economics and Policy, 31 (1), 69-92.

Hensher, D. A. and Plastrier V. E. (1985). Towards a dynamic discrete-choice model of household automobile fleet size and composition. Transport Research part B, 19(6), 481-495.

Li, T. Dodson, J. and Sipe, N. (2011). Investigating private motorised travel and vehicle fleet efficiency: Using new data and methods to reveal socio-spatial patterns in Brisbane. State of Australian Cities conference, 29 November - 2 December 2011, Melbourne, Australia.

Li, T. Corcoran, J. Pullar, D. Robson, A. and Stimson, R. (2009). A Geographically Weighted Regression Method to Spatially Disaggregate Regional Employment Forecasts for South East Queensland, Applied Spatial Analysis and Policy, 2, 147-175.

Litman, T. (2005). Evaluating transportation equity: methods for incorporating distributional impacts into transport planning. Victoria Transport Policy Institute, Canada.

Mannering, F. and Winston, C. (1985). A dynamic empirical analysis of household vehicle ownership and utilization. The RAND Journal of Economics, 16(2), 215-236.

Manski, C. F. and Sherman, L. (1980). An empirical analysis of household choice among motor vehicles. Transportation Research Part A, 14(6), 349-366.

Mccarthy, P. and Tay, R. (1998). New vehicle consumption and fuel efficiency: a nested logit approach. Transport Research part E, 34(1), 39-51.

Mulley, C. and Tanner, M. (2009). The Vehicle Kilometres ravelled (VKT) by Private Car: A Spatially Analysis Using Geographically Weighted Regression. Australasian Transport Research Forum, Auckland, New Zealand.

Paez, A. (2006). Exploring contextual variations in land use and transport analysis using a probit model with geographical weights. Journal of Transport Geography, 14, 167-176.

Paez, D. and Currie, G. (2010). Key Factors Affecting Journey to Work in Melbourne using Geographically Weighted Regression. Australasian Transport Research Forum, Canberra, Australia.

Paleti, R. Eluru, N. Bhat, C. R. Pendyala, R. M. Adler, T. G. and Goulias K. G. (2011). Design of comprehensive microsimulator of household vehicle fleet composition, utilization, and evolution. Journal of Transportation Research Board, 2254(2), 44-57.