The Spatial Interactions between Public Transport Demand and Land Use Characteristics in the Sydney Greater Metropolitan Area

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ABSTRACT
This paper presents a public transport demand model incorporating land use density, diversity, design, and accessibility to examine the relationship between public transport demand and land use characteristics in the Sydney Greater Metropolitan Area. A Geographically Weighted Regression approach is employed to identify the spatial variation of the land use variables and their impacts on public transport demand at a Travel Zone level. The global model of Geographically Weighted Regression suggests that increasing land use density and walkability as well as providing a better accessibility to the Sydney Central Business District have positive impacts on public transport demand. The local model of Geographically Weighted Regression shows that the impacts of the land use characteristics on public transport demand distinctively vary spatially, and the estimated parameters may have different signs in some areas as compared to the global model. This paper highlights the way in which the relationship between travel demand and land use is heterogenous over geographical space which cannot be captured by conventional multivariate regression models.

INTRODUCTION

The relationship between public transport demand and land use characteristics has been extensively examined in the existing literature. It has also been well recognised that the land use characteristics in a built environment can be categorised into land use density, diversity, urban design (known as 3D), and accessibility *(1)*. This paper provides empirical evidence of the relationship between public transport demand and land use characteristics as an evidence base for how public transport use can be increased through strategic urban planning.

Although the relationship between public transport demand and land use has been identified in the existing literature, there is a lack of micro-analysis which comprehensively incorporates all the land use factors (3D and accessibility) in the public transport demand model, together with other key determinants such as price and socio-economic factors. Previous studies, based on the regional level (e.g. cities; states; countries), have not been able to provide insights into spatial variation of different variables across local communities on public transport demand for a specific study area. Furthermore, the relationship between demand and land use has been conventionally examined at an average level assuming a homogenous parameter across all observations, without taking the spatial variability of land use variables into consideration. The spatial variability is important because it indicates a heterogeneous association between public transport demand and its determinants in the local areas, which provides important policy implications for local transport and urban planning.

This paper applies a Geographically Weighted Regression (GWR) methodology to investigate the relationship between public transport demand and land use characteristics in the Sydney Greater Metropolitan Area (SGMA) at the Travel Zone (TZ) level. A global public transport demand model incorporating comprehensive land use variables as well as price and socio-economic factors is constructed to identify the average relationship in the SGMA, and a GWR local model is estimated to investigate the spatial variability of this relationship.

LITERATURE REVIEW

Public transport demand is affected by various factors. Balcombe et al. *(2)* and a meta-analysis reported by Holmgren *(3)* suggested that public transport fare and users' socio-economic factors should be taken into account in public transport demand models. Cervero and Kockelman *(1)* also concluded that the 3D of land use and accessibility have significant impacts on the public transport use. In principle, density generally refers to housing, population, or employment density. Diversity is used to illustrate the heterogeneity of land use and is normally measured as the entropy of the land mix. Urban design refers to the connectivity and walkability in a neighbourhood environment, such as the number of intersections or the type of road network (e.g. grid or cul-de-sacs), whereas accessibility usually refers to the walking distance to the nearest public transport station or major town centres.

Comparing methodologies commonly used in this literature, the discrete choice modelling approach is the most widely adopted method (*1,4-8*). However, this approach focuses more on the individuals' mode choices between alternatives rather than the aggregate public transport demand within the study area. On the other hand, some studies employed multivariate public transport demand models based on household or regional geographies. (*1,9,10*). In general, most research results suggest that public transport use increases with higher density, diversity, accessibility, and more walking-supportive urban design. However, both choice modelling and multivariate regression studies assume a homogenous relationship between demand and land use so the spatial dependency of the variables cannot be observed. Spatial variability appears to be more important when analysing land use data. Wang et al.

(11) pointed out that land use factors tend to be correlated across space, and thus they combined the discrete choice modelling approach with GWR techniques to model the land use development changes in Austin, Texas.

The GWR approach which can effectively capture the spatial variability of parameter estimates was developed by Fotheringham et al. *(12)*. GWR takes account of the spatial dependency in the estimation process by weighting the observations according to their geographical locations. The first application of GWR in transport research was introduced by Du and Mulley *(13)* who investigated the association between land use value and public transport demand in the Tyne and Wear region in the United Kingdom. In modelling travel demand, Mulley and Tanner *(14)* applied the GWR approach to model the household vehicle kilometres travelled (VKT) in Sydney. In terms of modelling public transport demand, Chow et al. *(15)* used a mixed GWR approach to predict public transport demand in Broward County of Florida by accessibility to employment, car ownership, employment density, and the composition of population. However, although the GWR approach has been increasingly applied in travel demand studies, there is a lack of research explaining public transport demand by a comprehensive set of explanatory variables including price, socio-economic factors, as well as 3D and accessibility of land use. Thus, this paper addresses this issue by constructing a public transport demand model for the SGMA that incorporates different categories of variables as identified above.

METHODOLOGY

GWR estimates both a global model regression and a local model regression. The global model is a multiple linear regression model used to investigate the average relationship between the dependent variable and its predictors in the study area, whereas the local model is able to identify the spatial variations of the relationship across different local areas.

The global public transport demand model constructed for this analysis defines that public transport demand (Y) in a TZ (i) is determined by the public transport trip price (P_i), a vector of socio-economic factors (S_i), and a vector of land use variables (L_i) and an independent error term (ε_i) as specified in equation (1). Although typically double-logarithmic models are used, a linear functional form is chosen in this paper because the linear model implies an elasticity which varies with the corresponding public transport demand and the explanatory variable concerned, which better conforms to economic theory than a double-logarithmic model which assumes the elasticity is constant across all observations. The elasticity of variable k, evaluated at the mean, can be derived from the average demand $(\bar{Y})$ and explanatory variables $(\bar{X})$ by equation (2).

$$Y_i = \beta_0 + \beta_1 P_i + \beta_2 S_i + \beta_3 L_i + \varepsilon \tag{1}$$

$$\bar{e}_k = \frac{dY}{dX_k} \cdot \frac{\bar{X}_k}{\bar{Y}} = \beta_k \cdot \frac{\bar{X}_k}{\bar{Y}} \tag{2}$$

The main shortcoming of the global model is that all observations in the study area are equally weighted in the estimation process, and thus the relationship between the dependent variable and independent variables is homogenous. This assumption might be over-simplified when there is spatial heterogeneity across the observations. Therefore, the local model of GWR can be applied to accommodate the spatial effect by allowing heterogenous parameters for observations located in different geographical coordinates (u_i, v_i).

$$Y_i(u_i,v_i) = \beta_0(u_i,v_i) + \beta_1(u_i,v_i)P_i + \beta_2(u_i,v_i)S_i + \beta_3(u_i,v_i)L_i + \varepsilon \tag{3}$$

The local model employs a kernel weighting scheme in the estimation process as defined in equation (4). This paper uses an adaptive weighting approach which allows the same number of observations for each estimation when the observations are not regularly distributed in geographical space, so the bandwidth of a kernel is larger when the observations are sparser and is smaller when the observations are densely clustered *(16)*. The estimated parameters for a location (i) are more influenced by its surrounding areas than areas further away within a given bandwidth. As a result, the parameters of observations in different locations are different in space which captures the spatial heterogeneity of the observations.

$$w_i(u_i,v_i) = (1-(\frac{d_i(u_i,v_i)}{h})^2)^2 \tag{4}$$

where
w_i = geographical weight for an observation i
d_i = distance between the i_{th} observation and the location (u_i, v_i)
h = bandwidth

In short, the global model provides a general relationship between the dependent variables and its determinants without taking the spatial variation into consideration, so the results can only be interpreted as an average value for the study area. In contrast, the local model investigates the spatial heterogeneity of this relationship for each observation, and the results can be projected to a map to visualise this effect. The performance of the local model as compared to the global model can be identified through the Akaike Information Criterion (AIC) and adjusted R-squared value. AIC is used to optimise the bandwidth in the estimation, and a model with a lower AIC (lower by 3 is the rule of thumb) represents a better goodness of fit, taking account the complexity of the model *(16)*.

DATA ACQUISITION

Data sources

The dataset used in this paper consists of travel-related data and land use data. The travel-related data including public transport demand and trip price as well as the socio-economic factors of public transport users are retrieved from Sydney Household Travel Survey (SHTS) collected by the Bureau of Transport Statistics (BTS) of Transport for NSW. The SHTS has been undertaken continuously since 1997/1998, with approximately 8,500 people in 3,500 households recruited annually *(17)*. The respondents recruited in each wave of SHTS are independent and representative of the population in the SGMA, as shown in Figure 1, which comprises 2,418 TZs. The individual public transport records from 1997 to 2010 are pooled and aggregated to the TZ level according to their household locations. This yields a total number of 1,824 TZs with public transport trips identified. Public transport demand in this paper is defined as the average number of public transport trips made by a traveller (i.e. a traveller refers to a respondent making at least one trip using any trip mode) in a day from a TZ.

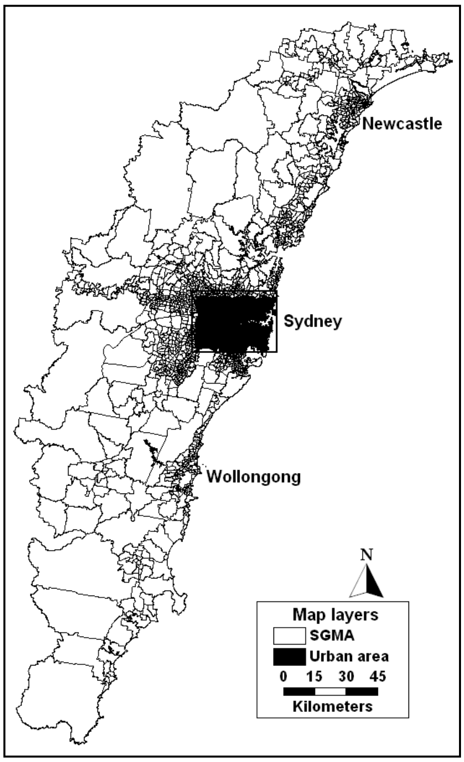

FIGURE 1 Map of Sydney Greater Metropolitan Area
(Source: developed from GIS maps)

The land use data are collected from Australian Census conducted by the Australian Bureau of Statistics (ABS) and from Geographical Information System (GIS) layers of the road network in the SGMA. The Australian Census is conducted at five-year intervals and the most recent data available in 2006 are merged into the SHTS database by matching geographical codes. The road network data used to retrieve other land use design variables and accessibility measure are based on the 2010 road network GIS layers provided by BTS. Whilst the most recent census data has typically been used for the land use variables (apart from where noted below), sensitivity analysis has been undertaken which compared the change in these variables over all possible census data for the time period covered by the dataset. This sensitivity analysis concluded that changes in land use variables happened only slowly so that the use of 2006 and 2010 data respectively does not introduce significant error.

Explanatory variables

As identified earlier, the literature on travel demand identifies price as one of the key determinants to predict demand, and the impact of price on demand provides important policy implications for transport operators and government sectors when setting the public transport fare policy. The trip price in this analysis is calculated for each separate public transport trip using the total ticket price reported by the respondents in the SHTS divided by the total number of trips provided by this ticket. There are many ticket types in Sydney including single tickets, return tickets, and periodical tickets. However, SHTS respondents only report their purchased ticket prices and ticket types and so a ticket journey multiplier is employed to identify the number of trips for periodical tickets *(18)* to approximate the ticket price for each single trip. This is then aggregated to the TZ level as an average public transport trip price for each TZ.

The socio-economic factors including personal income and age are taken from the SHTS database. All of these variables are recorded at an individual level so the average income and age of all public transport users in a TZ can be computed from the individual records. The inclusion of socio-economic factors in the demand model is not only to explain the variation of public transport demand, but also to mitigate the self-selection problem indirectly when attitudinal data are not available *(19)*.

As discussed above, the impact of land use characteristics on travel demand can be identified through 3D and accessibility. Land use density is defined by a function of population density and employment density to integrate the daytime activities and evening-time activities, and this composite variable also mitigates the strong multicollinearity problem between population and employment densities. The formula has been used by Wang et al. *(20)* as in equation (5). An average labour participation rate (LRP) of 0.62 from 1997 to 2010 retrieved from ABS *(21)* is used to convert residential population into number of employments. The combined density is defined as the number of population and employments within 800 meters of the centroid of a TZ. The 800 buffer is used instead of the population and employment per square kilometre to standardise the area size of a TZ.

$$\text{Combined density} = \text{employment density} + \text{population density x (LPR)} \tag{5}$$

The entropy of land use types is used to measure land use diversity. The entropy derived from equation (6) indicates the diversity of land use in a TZ. An entropy of zero represents extremely homogenous land use, whereas an entropy of one indicates the land use is equally heterogenous across all land use types. The dataset includes four land use types including agricultural and parkland, commercial, residential, and others.

$$ENTROPY = -\sum_{i=1}^{n} \ln P_i * (\ln P_i / \ln n) \tag{6}$$

where P_i =proportion of land use type i in a TZ
n =total number of land use types

Land use design can be observed from the connectivity and walkability of a local community. This paper uses the number of road links and pseudo nodes (which define changes in curvature of road links) within 800 meters of a TZ centroid to measure land use design. TZs with more road links are expected to provide better connectivity for walking and accessing public transport. Pseudo nodes are retrieved from the GIS layers of the road network and the denser the pseudo nodes, the more curvy are the roads. Pseudo nodes are also used to identify and define roundabouts, and cul-de-sacs in a local area. Figure 2 illustrates the composition of pseudo nodes in the GIS layer which represent two contrasting walking environments. In general, a built environment with more curvy roads and cul-de-sacs has more pseudo nodes than an area with a grid network, and lower walkability is associated with more pseudo nodes.

Accessibility to the Sydney Central Business District (CBD) is measured by the road distance between the centroid of a TZ to the CBD. This measure is considered to be important in explaining public transport demand in the context of Sydney, because the major public transport network focuses accessing the CBD area.

In summary, the dataset includes price, socio-economic variables, and land use variables covering 3D and accessibility to model public transport demand at the TZ level as shown in Table 1. This micro-level analysis allows for the identification of a global relationship between public transport demand and the explanatory variables in the SGMA as well as the spatial variation in space within the study area when using the GWR methodology.

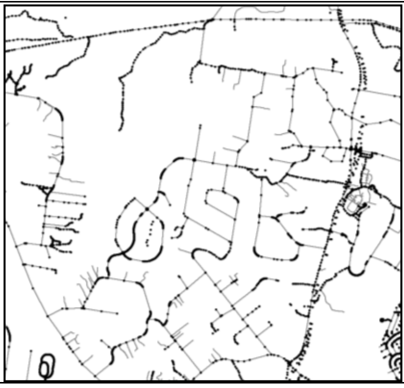

FIGURE 2(a) Pseudo nodes in a poor walking environment

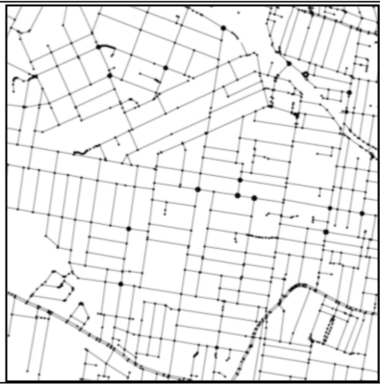

FIGURE 2(b) Pseudo nodes in a good walking environment

TABLE 1 Summary and Descriptive Statistics of Variables

Variable	Description	Unit	Source	Mean	Standard Deviation
Dependent variable					
PTTRIP	No. of public transport trips per person	Trips/person	SHTS	0.405	0.317
Price variable					
PRICE	Public transport trip price	AU dollars	SHTS	2.195	1.017
Socio-economic factors					
INCOME	Annual personal income	AU dollar (million)	SHTS	0.040	0.014
AGE	Age	Years	SHTS	43.947	5.800
Land use density					
DENSITY	Combined density of population and employment	Employments ('000)	Census	19.939	18.909
Land use diversity					
LANDMIX	Entropy of land use mix	n/a	Census	0.127	0.065
Land use design					
LINK	Number of road links within 800 meters of a travel zone centroid	Links ('000)	Road network	0.559	0.231
PSEUDO NODES	Number of pseudo nodes within 800 meters of a travel zone centroid	Nodes ('000)	Road network	1.601	1.715
Accessibility					
CBD	Distance between CBD and a travel zone centroid	km	Road network	29.637	29.073

MODEL ESTIMATION

The global regression model

The estimation results of the global model are displayed in Table 2. The F-test of the global regression model confirms the relationship between dependent variable and independent variables is statistically significant.

As this is a linear regression model, the interpretation of the estimated coefficients relates to the units of variables. The model estimation results suggest that all variables are significant with expected signs except for land use mix which is insignificant. Price, income, age, number of pseudo nodes, and distance to CBD have negative impacts on public transport demand, whereas density and number of road links have positive impacts.

TABLE 2 Estimation Results of Global Model

Variable	Coefficient	Standard Error	t-value	P-value
PRICE	-0.024	0.007	-3.57	0.000
INCOME	-2.364	0.492	-4.80	0.000
AGE	-0.004	0.001	-3.34	0.001
DENSITY	0.002	0.000	3.64	0.000
LANDMIX	0.116	0.100	1.16	0.248
LINKS	0.160	0.034	4.70	0.000
PSEUDO NODES	-0.026	0.004	-6.35	0.000
CBD	-0.004	0.000	-14.96	0.000
CONSTANT	0.747	0.069	10.84	0.000
Number of observations	1824			
Adj. R-square	0.26			
Akaike Information Criterion	459.71			
Prob > F	0.00			

The average elasticity is a convenient way to interpret the proportional change of public transport demand caused by the changes in the explanatory variables as shown in Table 3. By looking at the values of the average elasticities, age appears to be the most influential factor of public transport demand, with a one percent increase in age leading to a decrease in public transport demand by 0.44 percent on average. On the other hand, an increase of price and income will reduce public transport use as expected.

TABLE 3 Estimation of Average Elasticities

Variable	Coefficient	$\bar{Y}$	$\bar{X}$	Elasticity
PRICE	-0.024	0.405	2.195	-0.13
INCOME	-2.364	0.405	0.040	-0.23
AGE	-0.004	0.405	43.947	-0.44
DENSITY	0.002	0.405	19.939	0.08
LINKS	0.160	0.405	0.559	0.22
PSEUDO NODES	-0.026	0.405	1.601	-0.10
CBD	-0.004	0.405	29.637	-0.28

For the land use factors, the public transport use increases with higher density, but the elasticity of density at 0.08 appears to be lower than other factors. Land use entropy, as a measure of land use diversity, is not a significant explanatory variable in public transport demand. This is possibly because of the low levels of aggregation in this analysis. TZs located in the urban areas are generally smaller than the rural areas so the land use categories tend to be more homogenous in smaller TZs which may be confounding the results. This effect can be identified from Table 1 which shows the mean land use entropy is considerably low at 0.127.

The two measures of land use design are both significant. Increasing the number of road links by one percent will raise public transport demand by 0.22 percent. In contrast, increasing the number of pseudo nodes has an inverse impact on public transport demand, because this lowers the walkability of the built environment and is likely to encourage more car use rather than more public transport use. The distance to CBD appears to be the most influential factor of all land use variables, with a one percent increase in distance to CBD decreasing public transport demand by 0.28 percent on average. This suggests that people living closer to the CBD are more likely to use public transport than people in the outer areas.

GWR local model estimation

The goodness of fit of the GWR local model can be compared with the global model using AIC and adjusted R-square values. The estimation results suggest that the AIC and adjusted R-square are 206.13 and 0.41 respectively, and both are improved as compared to the global model (i.e. AIC: 459.7 and adjusted R-square: 0.26 in the global model). This confirms that the local model has better model explanatory power and goodness of fit by taking account of the spatial heterogeneity of the observations. The Monte Carlo test can be used to examine the significance of the spatial variability of parameters identified in the local model. The results shown in Table 4 suggest that apart from income, age, and land use mix, all other variables have significant spatial variability of parameter estimates.

TABLE 4 Results of the Monte Carlo Test for Spatial Variability

Variable	P-value
PRICE	0.000
INCOME	0.230
AGE	0.080
DENSITY	0.000
LANDMIX	0.380
LINKS	0.010
PSEUDO NODES	0.000
CBD	0.000
CONSTANT	0.000

The GWR local model estimates the parameters for each observation, and the results can be displayed on GIS layers to visualise the spatial variation. The spatial variation of this analysis is only apparent in the urban area close to the Sydney CBD, so only the Sydney urban area as highlighted in Figure 1 is displayed in this section for discussion.

The estimated parameters of price, density, pseudo nodes, and distance to CBD are presented in Figures 3 to 6. TZs with significant parameters are highlighted in colour, with positive signs coloured in green and negative signs coloured in red. The grey areas and white areas are TZs with insignificant parameters or no public transport observations respectively.

As shown in Figure 3, price has a significantly negative impact on public transport demand in the North Sydney areas, but this impact decreases with the increase of distance to the CBD. The estimated parameters of price in these negative areas are larger in absolute values than the global parameter of price at -0.024, suggesting that public transport users in these TZs are more sensitive to the price change than the average in the SGMA. It is also important to note that in the south of the CBD, there is an area which has a significantly positive relationship between public transport demand and price. This is possibly because the railway line "Airport Link" serving between the CBD and this area is operated by a private sector, and there was an access fee for passengers using train stations between Sydney Airport and the CBD, even when the airport itself was not being accessed. Therefore, the train trip price in this area is higher than surrounding areas but with higher public transport demand.

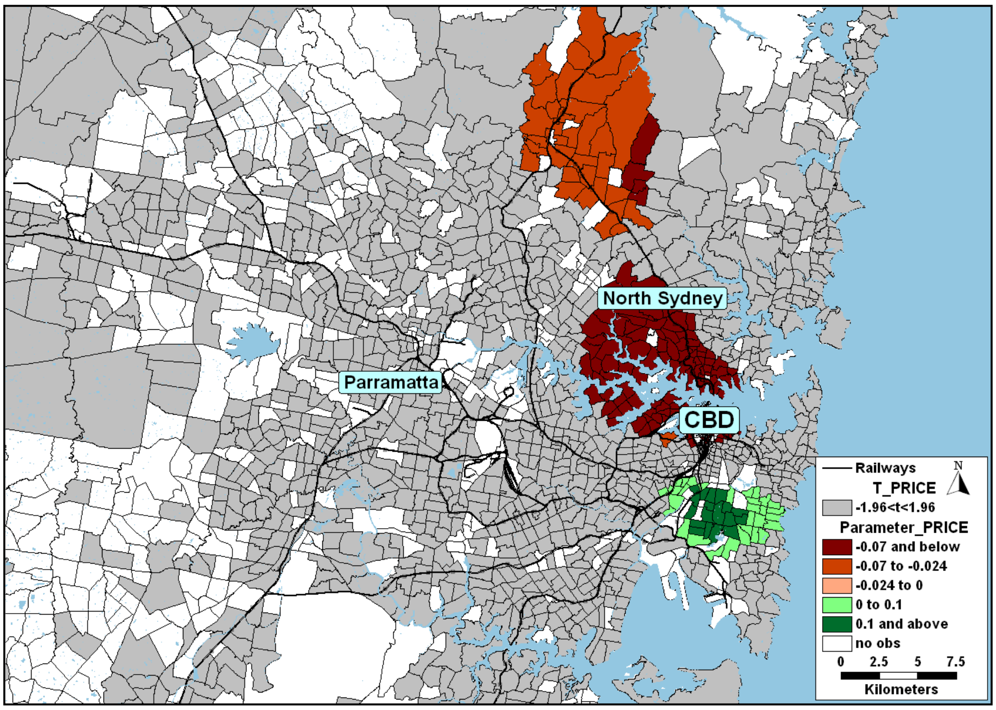

FIGURE 3 Map of the local model estimates of the price variable in the urban area

For the local estimates of pseudo nodes shown in Figure 4, TZs which have statistically significant parameters mostly have a negative relationship between public transport demand and the number of pseudo nodes, with larger parameters in absolute terms than in the global model at -0.026. In North Sydney and areas close to the CBD, the number of pseudo nodes has a positive impact on the public transport demand. This is because residents in this area highly rely on the public transport to access the CBD, but the local road network here consists of more curves and cul-de-sacs because of the topological features in these areas close to Sydney harbour.

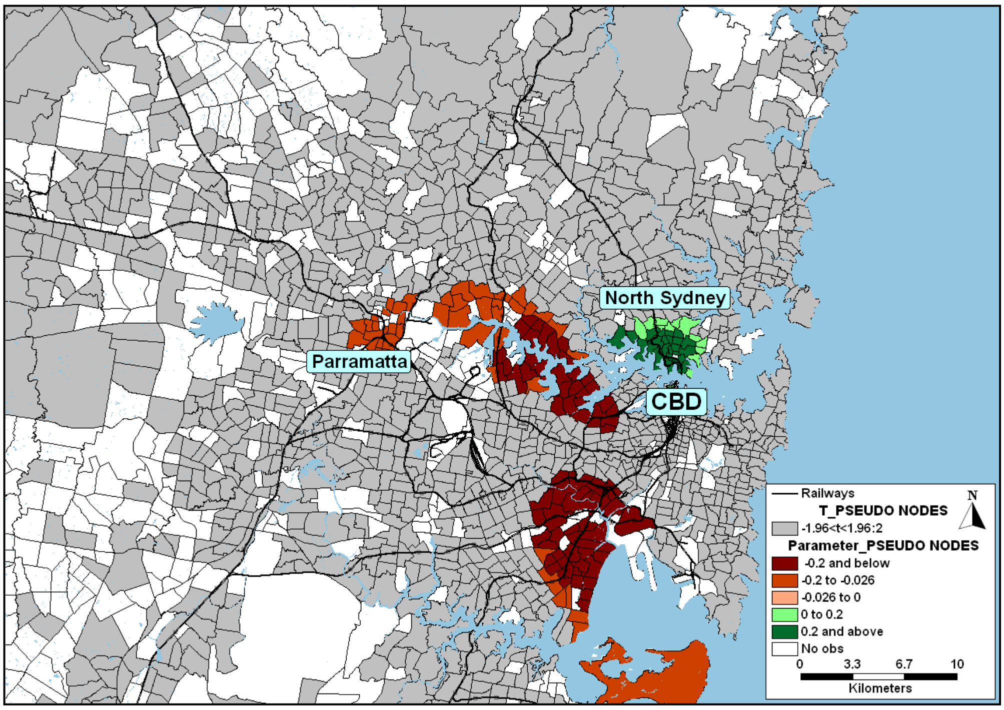

FIGURE 4 Map of the local model estimates of pseudo nodes in the urban area

For the distance to CBD, the negative relationship to the public transport demand is more transparent in the TZs closer to the CBD than in the outskirts of the city as shown in Figure 5. There is no TZ with a positive parameter and all the local parameters are larger in absolute terms than the global parameter suggesting that public transport users residing in inner Sydney are more sensitive to the travel distance to the CBD, as opposed to people living in the outer Sydney who may travel more frequently to local business centres instead of the CBD.

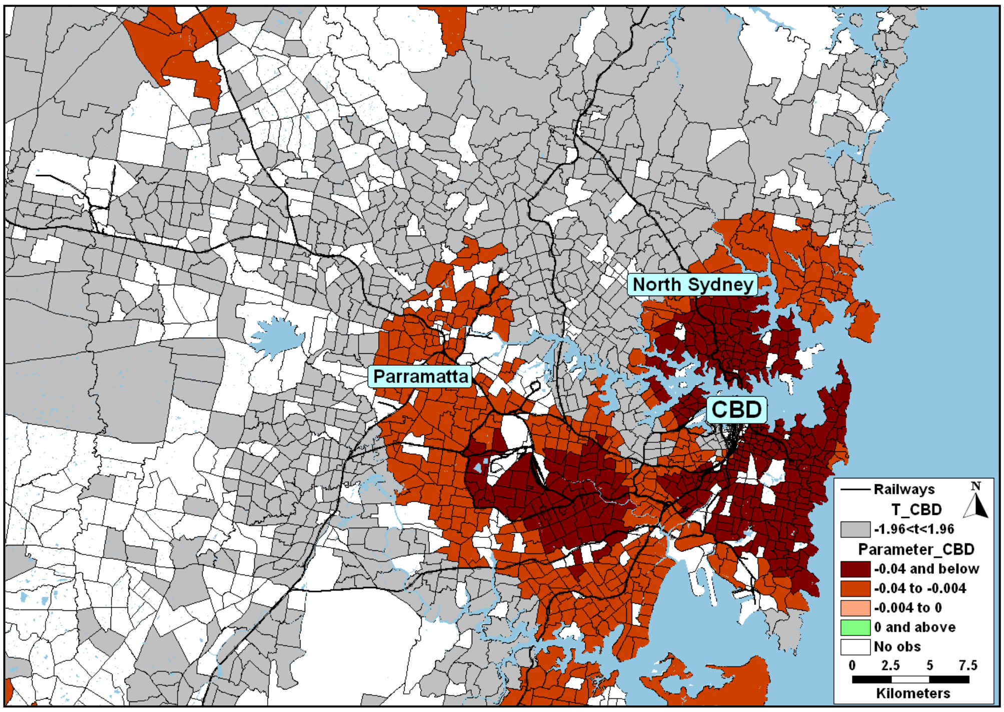

FIGURE 5 Map of the local model estimates of the distance to CBD in the urban area

The local parameter of combined density of employment and population is displayed in Figure 6. The inner Sydney and the west of Sydney show two distinctive patterns in a relationship of density to public transport demand. Higher density increases public transport trips in the west of Sydney but reduces public transport use in inner Sydney. In inner Sydney this maybe because the higher density of population and employment leads to more walking trips instead of public transport trips, as a result of the shorter travel distance between business and household locations. In contrast, the relationship is positive in the west of Sydney suggesting an increase in combined density of population and employment will raise public transport demand as expected from the global model estimation results. This distinctive difference between the two regions has important policy implications. Increasing density of population and employment through urban planning policies is expected to encourage more public transport use in the outskirts of Sydney, particularly in the western areas, as compared to inner Sydney where the population and employment are more saturated.

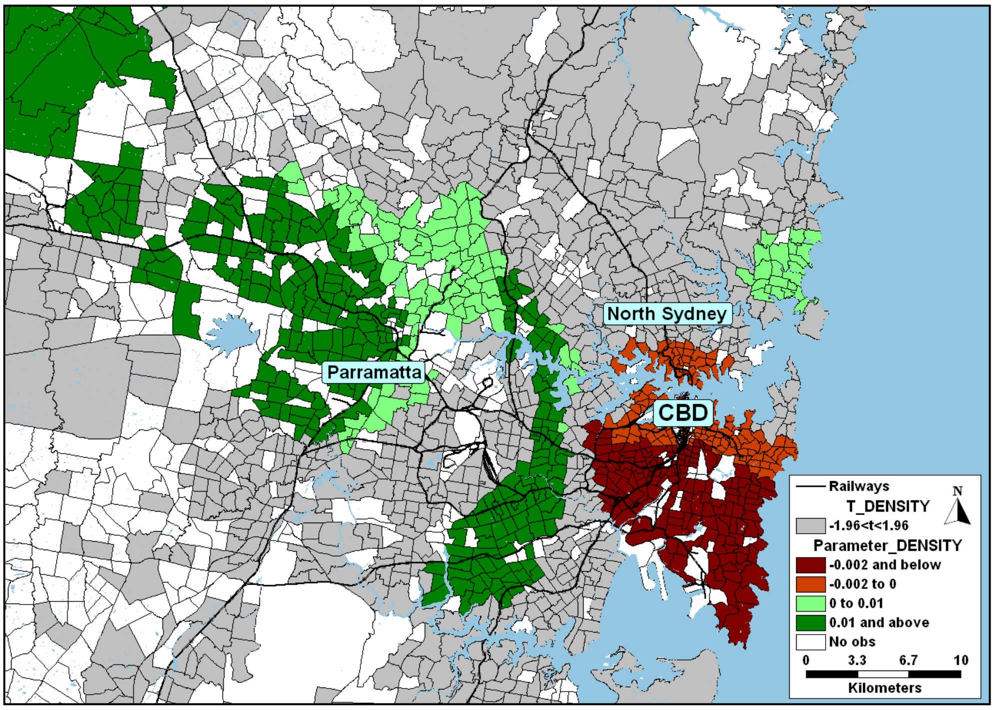

FIGURE 6 Map of the local model estimates of land use density in the urban area

In summary, the GWR local model gives more insight into the relationship between public transport demand and its explanatory factors at a disaggregate level, whereas the global model only suggests an average relationship within the study area. The investigation of the spatial variation of the local parameters provides important information and evidence for local transport and urban planning.

CONCLUSION

The global model which explains the average relationship between public transport demand and its determinants suggests that price, income, age, number of pseudo nodes, and distance to CBD have negative impacts on public transport demand, whereas density and number of road links have positive impacts. These results conform with findings of previous studies.

The local model estimation provides greater insight into the impact of explanatory variables on public transport demand because it takes account of the heterogenous spatial nature of the variables across the TZs. This paper demonstrates that the resulting estimated parameters vary in a statistically significant way across geographical space, and that these spatial effects are more evident in the urban area of the SGMA. In some TZs the parameters have inverse signs as compared to the global parameters as a result of local characteristics of land use or urban development.

This paper highlights the importance of understanding the relationship between public transport and land use factors at the local TZ level. The global model which has been widely applied in previous studies assumes that the estimated parameters are homogenous within the study area, masking spatial variation which can mislead transport and urban planning. The use of GWR provides a better understanding of the impacts of land use characteristics on public transport demand at a relatively disaggregate level and a better evidence base for policy making.

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REFERENCES
1. Cervero, R., and K. Kockelman. Travel Demand and the 3ds: Density, Diversity, and Design. *Transportation Research Part D*, Vol. 2, No. 3, 1997, pp. 199-219.
2. Balcombe, R., R. Mackett, N. Paulley, J. Preston, J. Shires, H. Titheridge, M. Wardman, and P. White. *The Demand for Public Transport: A Practical Guide*. Transport Research Laboratory: Wokingham, UK, 2004.
3. Holmgren, J. Meta-Analysis of Public Transport Demand. *Transportation Research Part A*, Vol. 41, No. 10, 2007, pp. 1021-1035
4. Cervero, R. Built Environments and Mode Choice: Toward a Normative Framework. *Transportation Research Part D*, Vol. 7, No. 4, 2002, pp. 265-284.
5. Rajamani, J., C. R. Bhat, S. Handy, G. Knaap, and Y. Song. Assessing the Impact of Urban Form Measures on Nonwork Trip Mode Choice after Controlling for Demographic and Level-of-Service Effects. . In *Transportation Research Record: Journal of the Transportation Research Board*, No. 1831, Transportation Research Board of the National Academies, Washington, D.C., 2003, pp. 158- 165.
6. Rodriguez, D. A., and J. Joo. The Relationship between Non-Motorized Mode Choice and the Local Physical Environment. *Transportation Research Part D*, Vol. 9, No. 2, 2004, pp. 151-173.
7. Zhang, M. The Role of Land Use in Travel Mode Choice: Evidence from Boston and Hong Kong. *Journal of the American Planning Association*, Vol. 70, No. 3, 2004, pp. 344-360.
8. Frank, L., M. Bradley, S. Kavage, J. Chapman, and K. Lawton. Urban Form, Travel Time, and Cost Relationships with Tour Complexity and Mode Choice. *Transportation*, Vol. 35, No. 1, 2008, pp. 37-54.
9. Kitamura, R., P. L. Mokhtarian, and L. Laidet. A Micro-Analysis of Land Use and Travel in Five Neighborhoods in the San Francisco Bay Area. *Transportation*, Vol. 24, 1997, pp. 125-158.
10. Cervero, R. Alternative Approaches to Modeling the Travel-Demand Impacts of Smart Growth. *Journal of American Planning Association*, Vol. 72, No. 3, 2006, pp. 285-295.

11. Wang, Y., K. M. Kockelman, and X. Wang. Anticipation of Land Use Change through Use of Geographically Weighted Regression Models for Discrete Response. . In *Transportation Research Record: Journal of the Transportation Research Board*, No. 2245, Transportation Research Board of the National Academies, Washington, D.C., 2011, pp. 111-123.
12. Fotheringham, A. S., C. Brunsdon, and M. E. Charlton. *Geographically Weighted Regression: The Analysis of Spatially Varying Relationships*. Wiley, Chichester, United Kingdom, 2002.
13. Du, H., and C. Mulley. Relationship between Transport Accessibility and Land Value: A Local Model Approach with Geographically Weighted Regression. In *Transportation Research Record: Journal of the Transportation Research Board*, No. 1977, Transportation Research Board of the National Academies, Washington, D.C., 2006, pp. 197-205.
14. Mulley, C., and M. Tanner. The Vehicle Kilometres Travelled (VKT) by Private Car: A Spatial Analysis Using Geographically Weighted Regression. *32nd Australasian Transport Research Forum*: Auckland, New Zealand, 2009.
15. Chow, L. F., F. Zhao, X. Liu, M. T. Li, and I. Ubaka. Transit Ridership Model Based on Geographically Weighted Regression. In *Transportation Research Record: Journal of the Transportation Research Board*, No. 1972, Transportation Research Board of the National Academies, Washington, D.C., 2006, 105-114.
16. Charlton, M., and A. S. Fotheringham. *Geographically Weighted Regression: White Paper*. National University of Ireland, Maynooth, County Kildare, Ireland, 2009.
17. Bureau of Transport Statistics. *2009/10 Household Travel Survey*. Bureau of Transport Statistics, Sydney, Australia, 2011.
18. CitiRail. *A Compendium of Cityrail Travel Statistics*. CityRail, Sydney, Australia, 2010.
19. Zhang, L. How Built Environment Affects Travel Behavior: A Comparative Analysis of the Connections between Land Use and Vehicle Miles Traveled in U.S. Cities. *World Symposium on Transport and Land Use Research WSTLUR 2011*: Whistler, Canada, 2011.
20. Wang, F., A. Antipova, and S. Porta. Street Centrality and Land Use Intensity in Baton Rouge, Louisiana. *Journal of Transport Geography*, Vol. 19, No. 2, 2011, pp. 285-293.
21. Australian Bureau of Statistics. *Labour Force Status by Sex - New South Wales - Trend, Seasonally Adjusted and Original.* Australia, 2012.