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Estimating land value uplift around light rail transit stations in Greater Kuala Lumpur: An empirical study based on geographically weighted regression (GWR)

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ABSTRACT

Introducing a rail transit system into an urban region is expected to increase land values, and subsequently, residential property values. Despite this general belief, little is known about the spatial distributional effects of land value uplift. Thus, the goal of this paper is to provide new insights on how proximity to light rail transit stations may affect residential property values in Greater Kuala Lumpur, Malaysia using geographically weighted regression (GWR). The results provide information on spatial variations in the effects of a light rail transit system on residential property values. This study utilises GWR to account for spatial heterogeneity and spatial dependence. The results suggest that residential property values benefit from the provision of a light rail transit system but with considerable spatial variation over a geographical area. Evidently, proximity to the nearest light rail transit station gives positive premiums of up to 8% for a majority of properties located in lower-middle and upper-middle income neighbourhoods such as Wangsa Maju, Setapak, Keramat, Setiawangsa, Ampang and Sentul. In contrast, the impact of proximity to the nearest light rail transit station for properties located in high-income neighbourhoods such as Petaling Jaya was found to be non-significant. These findings can assist policy makers to better understand how properties around light rail transit stations accrue benefits. However, since the benefit of a light rail transit system on nearby properties varies over a geographical area (and where a positive premium can swing from positive to negative depending on the area), it may be difficult for policy makers to impose a single-value tax if there is a land value capture policy to be considered for implementation.

1. Introduction

Investment in a rail transit system such as heavy or light rail is often promoted as a mechanism to improve accessibility to key employment centres, educational institutions, and leisure amenities. In social terms, rail transit investments not only provide equal transit mobility for people, but more importantly, improved personal mobility for disadvantaged groups (Baum-Snow & Kahn, 2005; Pucher, 2004). Moreover, rail transit investments also bring a variety of benefits which address more modern concerns such as promoting physical activity (MacDonald, Stokes, Cohen, Kofner, & Ridgeway, 2010) congestion relief (Karpouzis, Rahman, Tandy, & Taylor, 2007), reduction in per capita road-traffic accidents (Lalive, Luechinger, & Schmutzler, 2013), reduction in greenhouse gas emissions (Lalive et al., 2013; Chen & Whalley, 2012), and transit-oriented development (Peng, Li, & Choi, 2017). Alongside the benefits cited above, one of the most significant indirect benefits of a rail transit investment is the impact on 'improved land' value in the form of residential property values. Rail transit investment improves accessibility of the property to key activity centres and normally makes locations near transit stations more attractive. This should therefore capitalise and improve land values, in a process referred to as land value uplift.

Since rail transit systems have been proven to offer significant positive externalities, many cities in the world have begun to develop their own rail transit systems. However, developing and updating public transport infrastructure (such as rail transit systems), is one of the most expensive, complex and far-reaching investment decisions governments face (Mulley, 2014). In a developing country such as Malaysia, public transport infrastructure expenditures are financed primarily from borrowing and using funds from the federal government. These funds usually come from consolidated taxation revenue. Yet in many cases, there is a budgetary constraint on the government with respect to expenditures on public transport infrastructure. In addressing this constraint, one of the potential funding mechanisms that can be used is land value capture – a policy designed to capture land value increases that result from the provision of public transport

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infrastructure (Smith, Gihring, & Litman, 2009, 2006; Medda, 2012; van der Krabben & Needham, 2008). In an age of widespread fiscal restraint, land value capture and other alternative sources of capital have become increasingly attractive options for financing public transport that involve contributions from a range of public and private stakeholders (Zhao & Levinson, 2012). To assess whether a land value capture policy is feasible, information about land value uplift following a public transport infrastructure investment is required. This is due to the fact that property values should reflect, at any point in space, the combined influence of positive and negative externalities linked to the proximity of a nearby rail transit station.

The purpose of this paper is therefore to capture land value uplift for residential properties around light rail transit stations in Greater Kuala Lumpur, Malaysia. The null hypothesis is that proximity to the nearest light rail transit station has no positive effect on residential property values. Knowledge about land value uplift around rail transit stations in the Greater Kuala Lumpur metropolitan area (with its increasing and sprawling population) is important, as it helps to shed light on the promise of public transport networks for supporting the sustainability of the city's future development and the potential for planning future rail transit investments. The findings from this paper are useful to urban planners and policy makers, both in Greater Kuala Lumpur and around the world, who are increasingly looking to apply land value capture policy as a potential funding mechanism for the operation and construction of rail transit projects. In particular, they are useful for the estimation of value increments caused by rail transit systems. They are also useful in ensuring land value capture policy captures the actual changes in land values caused by a given project. Land value uplift is also an important category of information for potential developers and home buyers, who might target land and property around light rail transit stations. They might consider such properties as representing a good return on investment. This paper therefore contributes to the existing literature by providing empirical evidence about land value uplift around light rail transit stations in the context of a developing country and by considering the spatial distributional effects of land value uplift.

The paper begins by reviewing the relevant literature with respect to the development of an understanding of the relationship between proximity to rail transit systems and residential property values. Methods used to investigate land value uplift around light rail transit stations are then described and the principal findings are reviewed and discussed. Policy implications are explained and some limitations are highlighted.

2. Literature review

The theoretical basis for understanding the relationship between accessibility and land values has been based on the land rent theory developed by Alonso (1964), Muth (1969) and Mills (1972). This theory suggests that any significant improvement in the transportation system (such as with a rail transit system), should be reflected in the higher values of land along the rail transit corridor as compared to land outside the corridor. These higher land values would be the result of increased accessibility to key employment centres (normally in a central business district), educational and leisure amenities, and reduced transportation costs. This is especially so in places with superior access, namely, around a station. In urban contexts, these accessibility benefits should create a locational advantage, hence, helping to motivate individuals and firms to outbid one another for the land around a station (Mills & Hamilton, 1994). As a result, a bid-rent surface that peaks at transit stations might be expected.

Numerous literature reviews of the property value effects of public transport have been published (Diaz, 1999; Higgins & Kanaroglou, 2016; Huang, 1994; RICS, 2002; Ryan, 1999; Smith et al., 2006, 2009; Vessali, 1996). These reviews involved a survey of over 100 references mostly from North America, and have focused primarily on the effect of rail transit systems (heavy and light rail). Reviewers have concluded that although the results are mixed (and include positive, negative and non-significant results), most of these studies found significant positive relationships between proximity to transit stations and residential property values. A number of key principles identified from previous studies are summarised below:

2.1. Catchment areas

In investigating land value uplift around rail transit systems, previous studies have operationalized accessibility indirectly through measures of proximity to transit stations, in order to capture the bid-rent surface as a proxy for underlying accessibility benefits. Most studies seem to employ catchment areas relatively close to the transit stations using a radial distance of a 0.4 km, up to 1.6 km, or a walk time of between 10 and 20 min for residential properties (Forouhar, 2016; Forouhar & Hasankhani, 2018; Lewis-Workman & Brod, 1997). This is due to the fact that the impact area for residential properties seems to be wider compared to commercial properties.

2.2. Treatment of time

Another important observation from previous studies is treatment of time. Most studies have investigated the effect on residential property values immediately after the service began and decades after (as the full benefits are recognised). Researchers have investigated how the announcement of a rail project by government, and the subsequent anticipation of improvements in transport infrastructure by home buyers, affected residential property values (Gatzlaff & Smith, 1993; Golub, Guhathakurta, & Sollapuram, 2012; Henneberry, 1998; Kim & Lahr, 2013). Researchers have also investigated how the construction phase of a transport infrastructure project may influence a home buyers' inclination to purchase a property due to the noise, pollution, and inconvenience generated by such projects (Golub et al., 2013; Kim & Lahr, 2013).

2.3. Methods and data

The literature has also shown that most studies employ a hedonic pricing model to capture property value effects of rail transit, using residential transaction prices or apartment rent prices as the dependent variable. In cases where residential transaction price data are unavailable due to confidentiality, asking prices are normally used (see Du & Mulley, 2007). However, a hedonic pricing model is subject to criticism due to its insensitivity in taking into account the spatial heterogeneity and potential spatial dependence between variables (So, Tse, & Ganesan, 1997). Only recently and with the evolution of spatial analysis technology, have researchers begun to consider spatial interactions. This allowed the impact of rail transit and other variables to vary over a geographical area using geographically weighted regression (GWR) (Du & Mulley, 2007; Dziauddin, Powe, & Alvanides, 2015).

Table 1 shows a summary of selected empirical studies on the impact of rail transit systems on residential property values since the 1990s, which also explained discrepancies in the findings based on a number of key factors. These empirical studies provided researchers with ample evidence for observing how rail transit systems have affected residential property values. In general, the studies have indicated that proximity to transit stations have a positive and statistically significant effect on residential property values. However, the magnitudes of these effects can be small or large. For example, in North America Bowes and Ihlanfeldt (2001) found properties within one-quarter mile decreased by 19% compared with properties beyond three miles. Cervero and Duncan (2002) claim that single-family properties and condominiums experience a price premium when located near commuter rail, and a negative or modest premium when located near a light rail station. Consistent with these findings, more recent studies by

Table 1
Summary of selected studies on the effects of rail transit systems on residential property values.

City (transit system) *Authors*	Findings	Impact Factors
Atlanta (MARTA) Nelson, 1992	Property values increased in low-income neighbourhoods by US $1045 for every 100 feet closer to the East Line but decreased by US$965 for every 100 feet closer to the East Line in high-income neighbourhoods	Low-income households rely more heavily on rail transit than those who are more affluent
Miami (Miami Metro Rail) Gatzlaff & Smith, 1993	Property values slightly increased in high-income neighbourhoods but unaffected in low-income neighbourhoods	Low-income households are less likely to respond to rail transit project announcement
Greater Manchester (Metrolink) Forrest, Glen, Grime, & Ward, 1996	Rail transit has no statistically significant positive effect on property values	The distribution on stations does not reflects today's pattern of urban activities, but that of one hundred years ago
Sheffield (Supertram), Henneberry, 1998	Rail transit has negative effect on property values when Supertram route was announced but unaffected after full opening	The negative effect may due to expectations of disruption during construction and it may take much longer for the benefits of rail transit to be appreciated by home buyers
Portland (MAX) Chen et al., 1997	Property values decreased by US$32.20 for every metre away from station beginning at a distance of 100 m from station	The accessibility effect far superior than the negative nuisance effect such as noise and traffic congestion around station
Atlanta (MARTA) Bowes & Ihlanfeldt, 2001	Property values between one to three miles from stations increased relative to comparable properties located more than three miles; Property values within one-quarter mile decreased by 19 per cent compared with properties beyond three miles	Properties located too close to stations suffered from negative externalities arising from neighbourhood crime, but those at an intermediate distance are beyond the negative externality effects and benefit from rail transit since it attract retail businesses and reduce commuting costs
San Diego (San Diego Trolley) Cervero & Duncan, 2002	Single-family homes and condominiums garnered higher premium when located near Coaster Commuter Rail (East Line) compared to an identical properties located near light rail (South Line)	Premiums dominated greatly by property type and rail transit type
Seoul (Subway Line 5) Bae et al., 2003	Property value increased only before the line's opening	The city has a dense subway system. As a result, locations do not differ widely in terms of access to rail transit
Beijing (Metro Line 2) Tian, 2006	Property values decreased by ¥5449 for every 1-min increase in walking distance from rail transit station	Public transport such as rail transit has been dominant in denser city, thus can have substantial influences on real estate markets
Newcastle-Sunderland (Sunderland-Tyne and Wear Metro) Du & Mulley, 2007	Rail transit (Metro) has minimal and varied significant positive effect on property values over geographical area	Co-ordinated land use policies, available land for development, regional economic trends and favourable social and physical conditions affect the degree of impact
Buffalo (Light Rail System) Hess & Almeida, 2007	A home located within one-quarter of a mile radius of a light rail station can earn a premium of US$1300-3,000, or 2–5 per cent of the city's median home values; Proximity effects are weakly positive in high-income stations areas and negative in low-income station areas	Where access to rail transit is not highly valued, property values do not rise; Lack of regional accessibility to employment centres, lack of development within station areas, fragmented planning process for metro rail, and lacked of co-ordination between New York State and local municipal planning negatively affect the potential positive impact
Phoenix (Light Rail Transit System) Golub et al., 2012	A single-family home located within 200 feet from station decrease in value but those located between 201 and 3000 feet will increase in value at the different time periods; A multi-family home values increased for every feet closer to station at the different time periods	Decrease in value within 200 feet results from a nuisance effect, whilst increase in value results from the accessibility benefit of being proximate to station
Montreal South Shore (Commuter Rail) Dubé et al. (2013)	Property located within 0–500 m and 1000–1500 m radius from station yield a premium of 9.7 per cent and 2.7 per cent respectively; Property located within less than 2 min, 2.1–4 min, and 4.1–6 min drive from station yield a premium of 6.2 per cent, 4.7 per cent, and 3.7 per cent respectively but non-significant at 12 min and beyond	The system has had significant effect on accessibility to city centre
Jersey (Hudson-Bergen Light Rail) Kim & Lahr, 2013	Annual price appreciation increased by 16.9 percentage points for properties located near the West Side Avenue station, 20 percentage points East 22nd Street station, non-significant effect Begernline Avenue station	The newly created accessibility by Hudson-Bergen Light Rail is capitalised at stations farthest from city centre; Non-significant effect for properties around Begernline Avenue station because of it is located in Union City where the bus network to Manhantan is already superior
Greater Kuala Lumpur (Kelana Jaya Line) Dziauddin et al., 2015	Light rail transit has varied significant positive effect on property values over geographical area indicates that the system may have a positive effect on residential property values in some areas but negative in others.	The system has had significant effect on accessibility to city centre for some areas; Non-significant effects for properties in some areas because of households do not rely on rail transit to travel to city centre and due to nuisance effects.
Scania (Commuter Rail) Bohman & Nilsson, 2016	Property values increased in low-income market segments	Low-income households rely more heavily on rail transit than richer groups
Tehran (Metro Rail System) Forouhar, 2016	Property values decreased in high-income neighbourhoods but increased in low-income neighbourhoods	Negative effect in high-income neighbourhoods is due to lack of considerable demand for public transport, inappropriate land-use management, perceptions of crime and privacy, and nuisance effects; Low-income households rely more heavily on rail transit than richer groups
Dubai (Metro) Mohammad et al., 2017	The effect is about 13 per cent within 701–900 m of a metro station, but it is estimated to be −9 per cent and −17.7 per cent within 0.5 km from station	Negative externalities associated with noise and pollution from the transport system has affected properties located too close to metro station
Tehran (Metro Rail System) Forouhar & Hasankhani, 2018	Property values increased in low-income neighbourhoods but decreased in high-income neighbourhoods	The need for public transportation, land use planning and management, socio-cultural effect and possible nuisance effects identified as the contributing factors

Golub et al. (2012), Dubé, Thériault, and Des Rosiers (2013) and Kim and Lahr (2013) have also found significant positive relationships between rail transit systems and residential property values. However, Hess and Almeida (2007) have found less profound significant positive effects of rail transit on property values in Buffalo, New York. Although the impact of rail transit systems in the United Kingdom (UK) is generally seen as positive, little emphasis has been placed on quantifying these positive effects (Chesterton, 2000; Forrest, Glen, Grime, & Ward, 1996; Henneberry, 1998). Meanwhile, studies carried out in other places have also found that rail transit systems have a significant positive effect on residential property values (Bae, Jun, & Park, 2003; Bohman & Nilsson, 2016; Dziauddin et al., 2015; Forouhar, 2016; Forouhar & Hasankhani, 2018; Mohammad, Graham, & Melo, 2017; Tian, 2006).

While most studies found significant positive effects on residential property values, a few studies have determined a negative effect with respect to station proximity (Chen, Rufolo, & Dueker, 1997; Forrest et al., 1996; Henneberry, 1998). However, other studies have found insignificant effects with respect to station proximity (Gatzlaff & Smith, 1993). Whilst this paper focuses on rail transit systems, it is important to recognise that a bus-based public transit system is also likely to bring about premiums with respect to property values (Dubé, Des Rosiers, Thériault, & Dib, 2011; Mulley, 2014; Perk, Bovino, Catalá, Reader, & Ulloa, 2013). In addition, despite the vast majority of studies having investigated the impact of rail transit systems on residential property values, there has also been research conducted on the relationship between rail transit and commercial office and industrial property values (Golub et al., 2012; Ko & Cao, 2013; van der Krabben & Needham, 2008). These have generally demonstrated significant positive relationships.

In summary, findings from the previous studies shown in Table 1 indicate that the impact of rail transit systems on residential property values depends on a number of factors, including: (a) accessibility impacts of transit improvements; (b) the type of transit system and station facilities; (c) time treatment; (d) neighbourhood socio-economic status; (e) nuisance effects; (f) land use of station area; and (g) housing types. Therefore, estimating land value uplift around improved transport infrastructure requires an in-depth investigation that examines these key factors.

3. Method description

3.1. Study Area

Greater Kuala Lumpur is the largest urban centre in Malaysia and has witnessed significant population and economic growth over the past 30 years. This region is the centre of Malaysia's economic activity, with 37% of total gross domestic product (GDP) and contributing about MYR263 billion (US$84.8 billion) to gross national income (GNI) in 2010 (Inside Investor, 2012). Due to strong economic growth, the total employment in this region between 1990 and 2010 has increased from 1.4 million to 3.3 million, which was largely contributed by the services sector (i.e., accounting for approximately 60% of all new jobs creation in this region) (Department of Statistics, 1991; 2010).

With higher economic growth and rising income, there has been an increase in the number of registered vehicles. In 2011, there were more than seven million registered vehicles in the Greater Kuala Lumpur region alone (i.e., about 35% of Malaysia's registered vehicles). The number of vehicles presents significant challenges and issues, such as traffic congestion, limited parking space, fatal accidents and environmental deterioration. To meet these challenges, the government has embarked on major developments in land transport over the last 30 years. Although construction of highways and ring roads in and around the city has improved the traffic flow to some extent, the city centre is still plagued by daily peak morning and evening traffic jams (Mohamad, 2003). Another initiative taken by the government to curb traffic congestion includes the promotion of public transport (such as the light rail transit system), as a mode of urban travel.

The Greater Kuala Lumpur area has two light rail transit lines: the Ampang-Seri Petaling light rail transit line and the Kelana Jaya light rail transit line (see Fig. 1). The Ampang-Seri Petaling light rail transit line and the Kelana Jaya light rail transit line began their service in 1996 and 1998 respectively, and cost RM5.4 billion (1995 ringgit). The Ampang light rail transit line is broken up into two destinations which start at the Sentul Timur Station. The first route ends in Sri Petaling in the south, while the second course ends in Ampang in the eastern suburbs of the city, travelling a distance of 15 km and 12.4 km respectively. Meanwhile, the Kelana Jaya light rail transit line operates an approximate 27 km course from north to south between Kelana Jaya and Gombak and has 24 stations. Currently, the Ampang and Kelana Jaya light rail transit lines carry approximately 400,000 passengers per day (Prasarana Malaysia Berhad, 2015).

3.2. Land value uplift estimation

This paper combines a hedonic pricing model and GWR method to capture land value uplift around light rail transit stations. The hedonic pricing model captures the 'willingness-to-pay' for a variety of housing attributes such as structural, locational and neighbourhood attributes, by examining how buyers select the house that provides the best combination of attributes. The GWR method takes into account spatial heterogeneity and spatial dependence by accounting for geographical co-ordinates in the parameter estimates and the intercepts.

The hedonic pricing model is a technique that is widely used to analyse a market for a single commodity with many characteristics, with residential property being one such commodity. This technique was developed to account for the fact that the price of a marketed commodity is related to its characteristics. For example, when a buyer purchases a residential property, he/she pays for a bundle of characteristics associated with that property (Rosen, 1974). In terms of residential property modelling, the characteristics of properties usually include, but are not limited to, structural characteristics (e.g. dwelling age, floor size, number of bedrooms, number of bathrooms and dwelling ownership), locational characteristics (e.g. proximity to amenities) and socio-economic characteristics (e.g. unemployment rate and racial composition).

To many researchers, the hedonic pricing model has long been considered a powerful tool for real estate appraisal. Yet this technique is subject to criticism, because in the hedonic pricing model, the relationships between dependent and independent variables are assumed to be stationary (or homogenous) over a geographical area. In fact, spatial heterogeneity in the relationships between dependent and independent variables over a geographical area commonly exists in spatial data sets, and the assumption of homogeneous or structural stability may be highly unrealistic.

Although many past hedonic pricing studies attempted to control for spatial effects by increasing the sample size, including locational and socioeconomic attributes, measuring proximity from a given residential property to amenities with distance, and applying a hedonic pricing model to housing submarkets or to different types of properties, the nature of the spatial relationship between residential property prices and attributes has not been explicitly modelled (Dziauddin et al., 2015).

Following Basu and Thibodeau (1998), spatial econometric techniques have proven useful in addressing spatial heterogeneity and spatial dependence in the housing market. For the past 40 years or so, several spatial econometric techniques have been proposed and developed by researchers to enable the inclusion of spatiality within property models. Examples include the spatial expansion method (Casetti, 1972), multilevel modelling (Goldstein, 1987; Jones & Bullen, 1993, 1994), the spatial autoregressive model (also known as spatial lag model) (Anselin, 1988), and more recently GWR (Brunsdon, Fotheringham, & Charlton, 1996; Fotheringham, Brunsdon, & Charlton, 1998, 2002).

In contrast to the hedonic pricing model, where single parameter estimates are applied for the entire geographical area, GWR is an exploratory method that allows variations in relationships between dependent and independent variables over a geographical area to be measured within a single modelling framework. This can provide a way of accommodating the spatial context within which residential properties are located (Fotheringham, Brundson, & Charlton, 2002). The mechanism by which GWR captures spatial varying relationships is the calibration of a series of local models, where the local neighbourhood is defined by spatial kernel functions with fixed or varying bandwidth

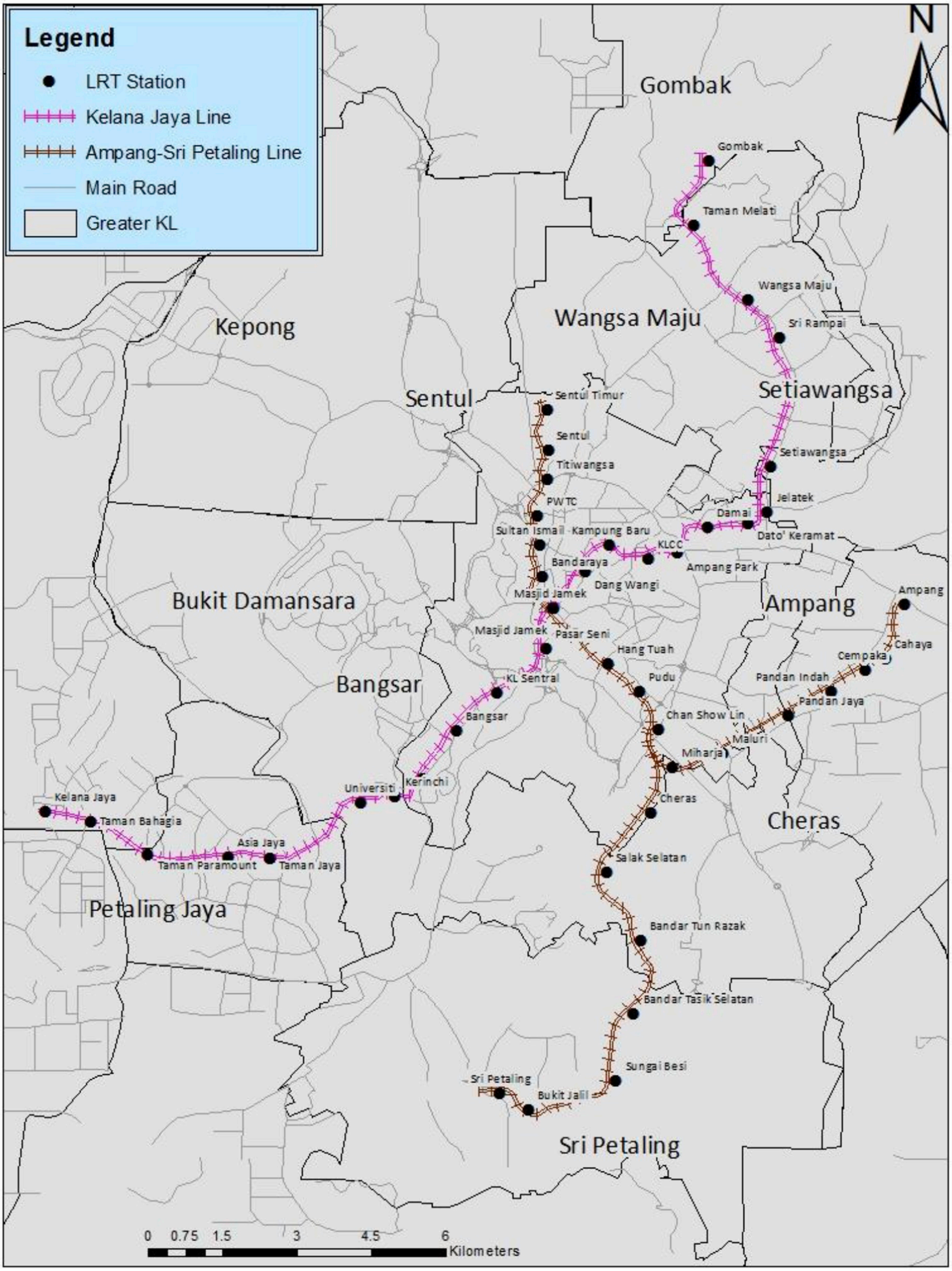

Fig. 1. The study area.
Source: Author's own work (2017)

(Fotheringham, Crespo, & Yao, 2015). There is now a range of applications for GWR in a wide variety of fields such as real estate (Fotheringham et al., 2015; Liang, Liu, Qiu, Jing, & Fang, 2018), health and disease (Chen, Wu, Yang, & Su, 2010; Nakaya, Fotheringham, Brunsdon, & Charlton, 2005), poverty (Benson, Chamberlin, & Rhinehart, 2005), urban public transport (Andersson, 2017; Cardozo, García-Palomares, & Gutiérrez, 2012), plant ecology (Wang, Ni, & Tenhunen, 2005; Zhao, Yang, & Zhao, 2010) and regional industrialisation (Huang & Leung, 2002; Partridge, Rickman, Ali, & Olfert, 2008). The intention in this paper is to use the hedonic pricing model in a novel way to explore and model spatial variations in land value uplift around light rail transit stations.

Building on a conventional global hedonic pricing model, GWR is used to calibrate local regression parameters by weighting the distance between one data point and another through the coordinates of data. By including longitude and latitude co-ordinates (u_i, v_i), the general form of the double-log hedonic pricing model employed in this paper can be mathematically expressed at location i in space as follows (Lu, Charlton, & Fotheringham, 2011):

$$lnY_i = \beta_0 (u_i, v_i) + \Sigma \beta_k (u_i, v_i) lnx_{ik} + \varepsilon_i, \quad (1)$$

where $\ln Y_i$ is the log dependent variable at location i, lnX_{ik} is the log value of the kth explanatory variable at location i, $\beta_0 (u_i, v_i)$ is the intercept parameter at location i, $\beta_k (u_i, v_i)$ is the local regression coefficient for the kth explanatory variable at location i, (u_i, v_i) is the co-ordinate of location i, and ε_i is the random error at location i. Note that a double-log is employed to enable interpretation of the coefficient and is the estimated percentage change in the dependent variable for a percentage change in the independent variable. A double-logarithmic form was selected because it generally gives a better fit in terms of the R^2 criterion and is intuitively interpretable.

Based on equation (1) above, location-specific parameters $\beta_k (u_i, v_i)$ are estimated using weighted least squares and can be expressed as follows (Lu et al., 2011):

$$\beta (u_i, v_i) = (X^T W (u_i, v_i) X)^{-1} X^T W (u_i, v_i) y \quad (2)$$

where X is the matrix of the explanatory variables with a column of 1s for intercept, y is the vector of the dependent variables, $\beta (u_i, v_i) = \beta_0 (u_i, v_i), \ldots, \beta_n (u_i, v_i)$ is the vector of $n+1$ local regression coefficients, and $W (u_i, v_i)$ is the diagonal matrix denoting the geographical weighting of each observed data for regression point i. By this geographically weighted calibration, continuous and smooth surfaces of local parameter estimates can be mapped over a geographical area.

3.3. Data acquisition

3.3.1. Residential property data

The data are based on actual transactions recorded in 2017 for residential property in the Greater Kuala Lumpur housing market. This cross-sectional data refers to the property located within a 1500 m radius (network distance) of light rail transit stations. The selection of this catchment area is guided by previous studies as discussed above. The average distance between observations to the nearest light rail transit station is approximately 916 m. In order to control for the impact of proximity to light rail transit stations on residential property values, the largest transacted housing type (namely, terraced property), has been chosen for analysis. In total, 264 units of terraced property-type data, together with their physical characteristics such as floor size (*FLOORSIZE*), lot size (*LOTSIZE*), number of bedrooms (*BEDS*), ownership status (*FREEHOLD*), corner lot type (*CORNERLOT*), and number of storeys (*STOREY*), were obtained from the Department of Valuation and Services, Malaysia (Kuala Lumpur, Shah Alam and Gombak branch). The Department of Valuation and Services officially records a property transaction once the stamp duty for the Sales and Purchase is paid. Although building age is expected to have a negative effect on property values, this important variable is not available from the data provider.

3.3.2. Locational attributes data

Data on the base map, land parcel and land use were purchased from the Department of Survey and Mapping, Malaysia. The data are believed to be of high quality and reliability as these data come from the professional body that provides maps and land use data in Malaysia. To measure the distance for a given observation to the locational amenities, the geographical information system (GIS) was used to position each observation accurately on a local map using geographical coordinates (latitude and longitude) obtained from Google Maps. The process of determining geographical coordinates from Google Maps was guided by housing address for each observation obtained from the Department of Valuation and Services Malaysia data set. GIS and spatial analysis were integrated into this paper, and the integration was particularly useful because the proximity from a property to the locational attributes was measured accurately using network distance. The distance in metres was measured along the street network by using a GIS program named Multiple Origins to Multiple Destinations, obtained from the Environmental Systems Research Institute (ESRI) support centre. The network distance measurement using this programme requires three layers of spatial data: points of origin (observations), points of destinations (locational attributes) and the road network data. This allowed the shortest route from each observation to the locational attributes to be calculated. Furthermore, the Multiple Origins to Multiple Destinations program allows more than one destination to be selected at any one time. Thus, proximity to locational attributes can be calculated simultaneously for each observation.

In this paper, locational attributes include proximity to the nearest light rail transit station (*LRT*), proximity to the Kuala Lumpur city centre (*CBD*), proximity to the nearest recreational park (*PARK*), proximity to the nearest primary school (*SCHOOL1*), proximity to the nearest secondary school (*SCHOOL2*), proximity to the nearest high-performance secondary school (*HPSCHOOL2*), and proximity to the nearest urban forest (*FOREST*).

Table 2 provides the summary statistics of dependent and independent variables employed in this paper. From the sample, property sales values range from MYR170,000 (US$42,500, with the FOREX rate at MYR4.00 or US$ 1.00 in 2017) to MYR2,300,000 million (US $575,000). The mean property sales value in this sample is MYR650,436 (US$162,609). From Table 2 we also learn that the average property has a floor area of around 1188 square feet. However, there are units with as low as 560 square feet to as large as 4286 square feet.

In all regression-based analyses, some independent variables are usually multicollinear. To manage this issue, the correlations among the independent variables used for the inclusion in the final models were detected by using Pearson's correlation coefficient and variance inflation factors (VIFs). Following Orford (1999) and Neter, Wasserman, and Kutner (1985), a Pearson's correlation coefficient above 0.8 and a variance inflation factor above 10 indicate harmful collinearity. In this paper, pairs of independent variables that produce a correlation coefficient higher than 0.8 and variance inflation factor of 10 or higher were eliminated from the final model. Another major concern in the application of regression-based analysis is the presence of heteroscedasticity. In this paper, the presence of heteroscedasticity was tested by performing the Park test. Based on the Park test that was performed,

Table 2
Descriptive statistics of dependent and independent variables.

	Units	Mean	S.D.
PRICE	MYR	650,435.61	302,881.25
LRT	Metre	916.32	373.77
FLOOSIZE	Square feet	1188.40	463.43
LOTSIZE	Square feet	1416.48	666.22
BEDS	Number	3.19	0.60
FREEHOLD	Dichotomous variable (0 or 1)	0.60	0.49
CORNERLOT	Dichotomous variable (0 or 1)	0.07	0.25
STOREY	Number	1.83	0.65
CBD	Metre	5398.44	2151.95
PARK	Metre	1533.09	539.11
MALL	Metre	1456.65	703.96
SCHOOL1	Metre	660.46	430.74
SCHOOL2	Metre	884.66	570.83
HPSCHOOL2	Metre	3001.83	1566.48
FOREST	Metre	2989.49	1246.42

it is safe to conclude that there is no heteroscedasticity in the error variance.

Since the GWR method follows a similar principle, it is sensible to expect the presence of multicollinearity among variables that have been estimated in the GWR model. Following Wheeler and Tiefelsdorf (2005), multicollinearity is more likely to be found in GWR models than in the hedonic pricing model. Wheeler and Tiefelsdorf (2005) argue further that: evaluating data in GWR for local multicollinearities and pair-wise correlations between sets of local coefficients is even more important than in the traditional global regression model due to the increased complexities of the GWR estimation procedure that potentially induces interrelationships among the local estimates (p.163). To overcome this, they suggest that scatterplots of pairs of local parameter estimates should be undertaken to investigate the presence of local multicollinearity. In this paper, the presence of local multicollinearity was first detected by using Pearson's correlation coefficient and followed by scatterplots; no significant multicollinearity between pairs of local parameter estimates was found.

3.4. Model specification

To estimate land value uplift around light rail transit stations, this paper uses a double-log specification, and its final form can be written as follows:

$$\begin{aligned}\mathrm{LnY_i} = {} & \beta_0 + \beta_1\mathrm{LnLRT_i} + \beta_2\mathrm{LnFLOORAREA_i} + \beta_3\mathrm{LnLOTRAREA_i} \\ & + \beta_4\mathrm{BEDS_i} + \beta_5\mathrm{FREEHOLD_i} + \beta_6\mathrm{CORNERLOT_i} + \beta_7\mathrm{STOREY_i} \\ & + \beta_8\mathrm{CBD_i} + \beta_9\mathrm{PARK_i} + \beta_{10}\mathrm{LnMALL_i} + \beta_{11}\mathrm{SCHOOL1_i} \\ & + \beta_{12}\mathrm{SCHOOL2_i} + \beta_{13}\mathrm{LnHPSCHOOL2_i} + \beta_{14}\mathrm{FOREST_i} + \varepsilon_i \end{aligned} \tag{3}$$

where Y_i is the sold price of a property in Malaysian Ringgit; *Ln* is the natural logarithm; *LRT is* proximity to the nearest light rail transit station measured in metres; *FLOORAREA* is the floor area of the property in square feet; *LOTAREA* is the land area of property in square feet; *BEDS* is the number of bedrooms; *FREEHOLD* is a dichotomous variable for property with freehold holding status; *CORNERLOT* is a dichotomous variable for property with corner lot type; and *STOREY* is the number of storeys. Finally, *CBD*, *PARK*, *MALL*, *SCHOOL1*, *SCHOOL2*, *HPSCHOOL2*, and *FOREST* are proximity to the Kuala Lumpur city centre, nearest recreational park, mall, primary school, secondary school, high-performance secondary school, and urban forest which were all measured in metres, respectively.

4. Empirical results: does residential property values benefit from light rail transit systems?

4.1. Hedonic pricing model (HPM)

Table 3 shows the results for the hedonic pricing model and GWR estimations. The hedonic pricing model gives a single set of parameter estimates and this single value is applied over a geographical area. On the other hand, the GWR model gives local parameter estimates for each observation point which includes minimum, maximum and average values. The regression results indicate that nearly 80% of the variance in the dependent variable is explained and have expected positive and negative signs, with the exception of proximity to the Kuala Lumpur city centre, nearest recreational park, and forest. Some insignificant variables in the hedonic pricing model may be locally significant in the GWR model. According to double-log specification, proximity to the nearest light rail transit station (*LRT*) has a positive effect on residential property values (though statistically insignificant). Hence, *ceteris paribus*, for every 100 m away from the nearest light rail transit station, residential property values decrease by about 4.3%. This equates to MYR3,036 ($US759), at the mean.

Among the considered physical characteristics, *FLOORAREA* and *LOTAREA* are the most statistically significant variables. So, *ceteris paribus*, for every square foot increase in the floor area, the property value increases by about 0.4%. This equates to a premium of MYR244 (US$61) at the mean. For every square foot increase in the lot area, the property value increases by about 0.4%. At the mean, this equates to a premium of MYR161 (US$41). These findings clearly indicate that the scarcity of space (floor and lot areas) leads to higher prices for additional floor and lot areas in this housing market.

Among locational attributes, proximity to the nearest recreational park (*PARK*) variable is the most statistically significant. The model suggests that, *ceteris paribus*, every 100 m increase in distance from the nearest recreational park (*PARK*) is associated with an 18.6% increase in property value, and this equates to MYR7,908 (US$1977), at the mean.

4.2. Geographically weighted regression

The previous section demonstrated the positive effect a transit station has on property values. However, this positive effect has been applied constantly across the geographical area. In contrast, GWR has

Table 3
Results of the hedonic pricing model and GWR (n = 264).

	Ordinary least square				Geographically weighted regression		
	Coefficient (β)	t-ratio	Sig.	VIF	Coefficient (β)		
					Min.	Max.	Mean
Intercept	5.647955	8.32	0.00**		5.937845	7.070795	6.437668
LRT	−0.042766	−1.58	0.12	1.67	−0.078999	−0.041822	−0.060473
FLOORAREA	0.445213	6.23	0.00**	4.00	0.307246	0.494213	0.406341
LOTAREA	0.350108	5.10	0.00**	6.48	0.218755	0.468096	0.333356
BEDS	0.265629	2.77	0.00**	2.14	0.224866	0.336655	0.265685
FREEHOLD	0.103931	2.07	0.04*	3.59	0.054423	0.090687	0.071628
CORNERLOT	0.018928	0.31	0.76	1.41	−0.152049	0.208777	0.010871
STOREY	0.071635	1.09	0.28	3.78	0.044657	0.118698	0.086663
CBD	0.204474	3.56	0.00**	4.14	0.172234	0.307529	0.234851
PARK	0.186408	4.68	0.00**	1.97	0.114586	0.264998	0.195428
MALL	−0.030024	−1.09	0.27	1.62	−0.096321	0.029260	−0.042966
SCHOOL1	−0.002363	−0.10	0.92	1.51	−0.039626	−0.007717	−0.031115
SCHOOL2	−0.016889	−0.58	0.56	2.20	−0.061516	0.054461	−0.007451
HPSCHOOL2	−0.118077	−3.86	0.00**	1.78	−0.176489	−0.128260	−0.148493
FOREST	0.008947	0.24	0.81	2.28	−0.103821	0.076362	−0.018785

Notes: Goodness of fit: Adjusted R^2 = 0.78 (hedonic pricing model); Adjusted R^2 = 0.80 (GWR). AIC = −52 (hedonic pricing model); AIC = −61 (GWR). The symbols * and ** denote a significance at the 5 and 1 per cent levels respectively.

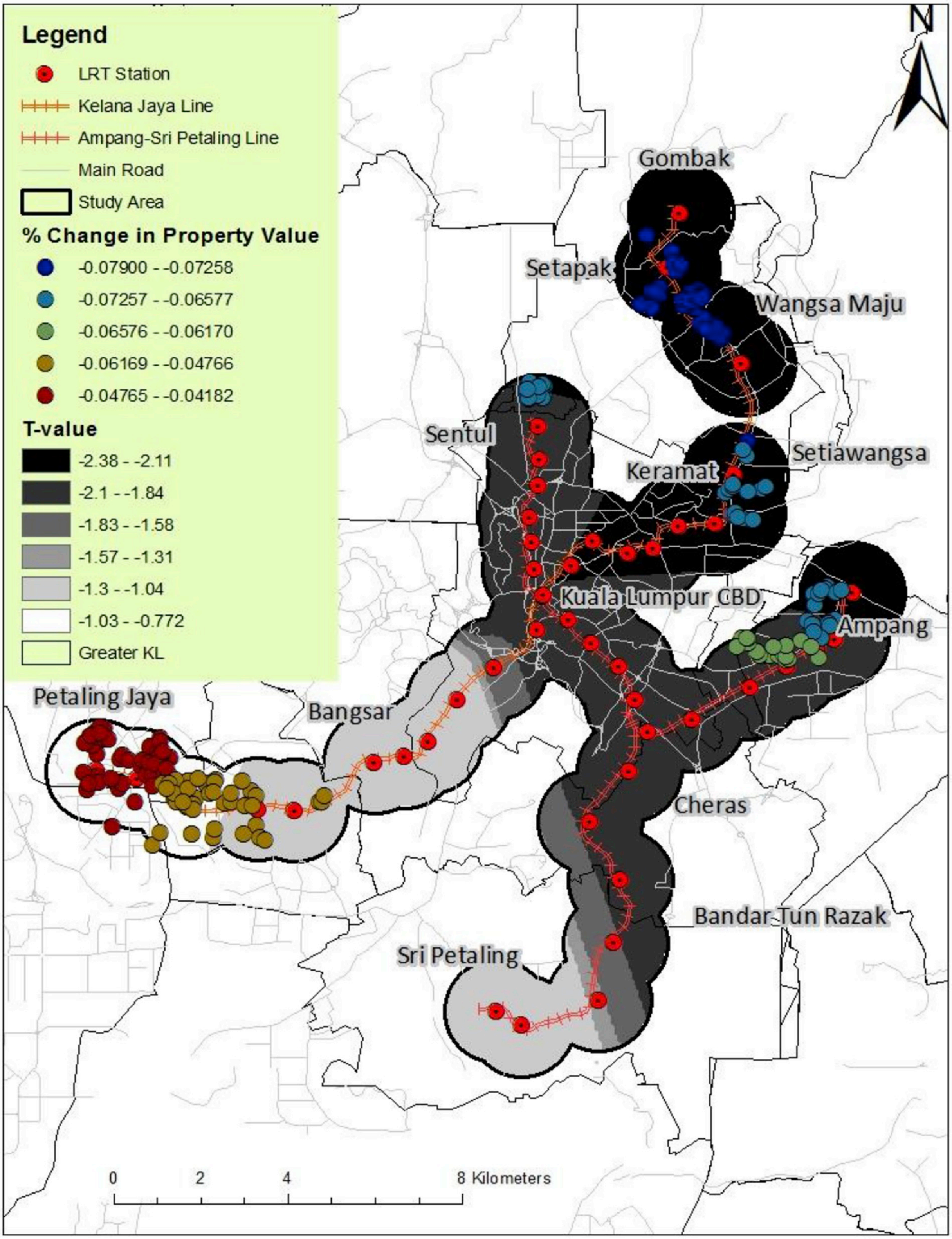

Fig. 2. Map of the local parameter estimates associated with variable *LRT*.
Source: Author's own work, 2017

the ability to produce a local parameter estimate for each relationship for each location. There are several versions of GWR software available and this paper uses the semi-parametric GWR 4.0 version (S-GWR 4.0) developed by Nakaya, Fotheringham, Charlton, and Brunsdon (2009, pp. 1–5). As for GWR model calibration, this paper uses adaptive bi-square spatial kernels which narrow the bandwidth where data are dense but allows it to spread where data are spread. It is important to note that the choice of bandwidth has a significant impact on the result of GWR. The Akaike information criterion (AIC) is usually used to identify the fitness of the bandwidth selection. When the AIC value reaches the minimum possible value, the optimized bandwidth is obtained (Akaike, 1974). However, when the sample size is small, the AIC is replaced by AICc for more accurate results (Burnham & Anderson, 2004). The diagnostic information from GWR analysis suggests the local model is performed better than the global model with a higher adjusted R^2 (0.80 over 0.78) and a lower AIC (-61 over -52).

Although all the local parameter estimates could be mapped, only proximity to the nearest light rail transit station variables (*LNDISTLRT*) is mapped here in order to save space, as this paper focuses primarily on the impact of light rail transit on terraced property values. Following Mennis's (2006) suggestion for mapping GWR results, this paper mapped the local parameter estimates alongside the local t-value (see Fig. 2) by inverse-distance-weighted interpolation with GIS. In this figure, the local parameter estimates are shown as dots of different colour. As shown in the Legend contained within Fig. 2, the negative parameter estimates indicate that as distance from the nearest light rail transit station increases, property value decreases, but with considerable spatial variation over a geographical area. Meanwhile, the local t-value is classified by six bands in which the darkest areas are significant, indicating positive property premiums. The lightest areas are non-significant negative t-values.

As Fig. 2 reveals, a non-significant positive impact for proximity to the nearest light rail transit station estimated by the hedonic pricing model is found to be significant for the majority of properties located in lower-middle and upper-middle income neighbourhoods such as Wangsa Maju, Setapak, Keramat, Setiawangsa, Ampang, and Sentul. *Ceteris paribus*, for every 100 m away from the nearest light rail transit station, residential property values decrease by between 6.2% (light green dots), and 7.9% (dark blue dots). At the mean, this equates to MYR4,379 (US$1095), and MYR5,608 (US$1402), respectively. This suggests the hedonic pricing model has underestimated the value associated with proximity to the nearest light rail transit station for some properties. This is in line with previous studies (Bohman & Nilsson, 2016; Forouhar, 2016; Forouhar & Hasankhani, 2018; Nelson, 1992) which state that lower-and middle-income groups rely more on public transport than those who are more wealthy, and thus attach a higher value to living in closer proximity to a station. Proximity to the nearest light rail transit station is insignificant for the majority of properties in high-income neighbourhoods in Petaling Jaya.

5. Discussion

The aim of this section is to discuss the contextual factors which provide insights with regard to the magnitude and direction of impact of proximity to light rail transit stations on residential property values between lower-middle, upper-middle income, and high-income neighbourhoods in Greater Kuala Lumpur. This paper suggests that the impact depends on the following contextual factors:

5.1. Increased demand for public transport

Private vehicle (car and motorcycle) ownership in Malaysia is among the highest in the world. In fact, according to the Nielsen Global Survey of Automotive Demand in 2014, car ownership among Malaysians is the highest in Southeast Asia, and Malaysia also has the highest incidence of multiple car ownership. It is reported that 54% of Malaysian households own more than one car. Among states in Malaysia, car ownership in Greater Kuala Lumpur is the highest. Yet, the costs of owning a car involve much more than the sticker price. In addition to the cost of purchasing a car, there are many other financial commitments that come along with owning a car. These include petrol, parking, toll charges, maintenance and repair costs. Moreover, for the past several years or so Malaysians have witnessed hikes in fuel and parking rates (especially in the Kuala Lumpur city centre). Given these conditions, it is not surprising that a 2016 survey done by the Land Public Transport Commission of Malaysia indicated that increasing numbers of people (especially those among low and middle-income groups), have begun to use public transport (including light rail transit) in order to minimise car ownership costs and traffic issues, particularly during peak morning hours. For example, that same survey shows the Kelana Jaya and Ampang-Sri Petaling Lines ridership has increased by 16% and 8%, respectively from 2015. In addition, a study conducted by Onn, Karim, and Yusoff (2014) in Greater Kuala Lumpur reveals that the likelihood of commuters using a car as their main mode of transport is significantly affected by parking costs, fuel prices and car prices. As a result, living close to the nearest light rail transit station in lower-middle and upper-middle-income neighbourhoods such as Wangsa Maju, Setapak, Keramat, Setiawangsa, Ampang and Sentul becomes an advantage, thereby driving up the value of properties at these locations.

5.2. Nuisance effect

Along with positive externalities, light rail transit can also produce negative externalities such as traffic congestion, noise, air pollution, safety issues, and visual clutter effects (particularly around transit stations), and therefore may negatively affect residential property values (Bowes & Ihlanfeldt, 2001; Forouhar & Hasankhani, 2018; Nelson, 1992). The insignificant impact found in high income neighbourhoods in Petaling Jaya can be associated with nuisance effects, particularly traffic congestion. Traffic congestion is related to passengers who use their own car to access a light rail transit station. Prior to the provision of park-and-ride facilities in late 2016, four out of five stations in Petaling Jaya did not have parking facilities. A study carried out by Ho, Ismail, and Rajagopal (2017) revealed that due to the absence of parking facilities, car owners were found to be illegally parking their cars by the roadside near stations and around the homes of local residents. This has caused serious traffic congestion around local neighbourhoods within close proximity to light rail transit stations. In addition, criminal activity might also increase in these areas and streets may also become less safe for children to ride their bicycles.

6. Conclusion and policy implications

Using a GWR model, this paper unequivocally shows that proximity to light rail transit stations is positively valued by the housing market in Greater Kuala Lumpur, Malaysia. Thus, the hypothesis that proximity to the nearest light rail transit station has no positive impact on residential property values is rejected. However, this positive impact varied across the study area, with lower-middle and upper-middle-income groups benefiting more than the high-income group. The findings in this paper support the general belief that public transport is often characterised as more important for low- and middle-income groups. Variation in the impact of a light rail transit system on residential property values by neighbourhood type in Greater Kuala Lumpur is in line with findings for other cities (Bohman & Nilsson, 2016; Forouhar, 2016; Forouhar & Hasankhani, 2018; Nelson, 1992). As demonstrated in this paper, a GWR model provides a tool for better understanding the direction and magnitude of the economic benefits of proximity to a light rail transit station, as well as identifying the likely recipients of these benefits.

These findings contradict those of Dziauddin et al. (2015), whose studies showed an opposite impact for proximity to Kelana Jaya light rail transit stations in Greater Kuala Lumpur. Based on 2004 and 2005 house price transactions data, they found that proximity to light rail transit stations has affected the majority of properties in Petaling Jaya, whereas they found insignificant effects for a majority of properties in Wangsa Maju and Setapak. This is perhaps unsurprising, both as a result of the reasons cited above and because of the results of previous studies which examined other locations (Bowes & Ihlanfeldt, 2001; Forouhar & Hasankhani, 2018; Forrest et al., 1996; Nelson, 1992). Such studies have demonstrated that nuisance effects generated around transit stations are likely to negatively affect surrounding property values in high-income neighbourhoods, as compared to low and middle-income neighbourhoods.

Given the challenges governments face with respect to the funding of public transport, it is important to reflect on the implications of this paper in terms of the potential to implement a policy of land value capture. A wide range of mechanisms have been used in many countries in an attempt to capture the increment in 'improved land' value that results from public transport investment. Most alternatives have significant shortcomings as land value capture tools. According to Walters (2012), countries such as Colombia, the UK, France and India continue to attempt land value capture through a betterment tax mechanism. This is due to the fact that the betterment tax is considered to be efficient, equitable and easily understood (Medda, 2012). Betterment taxes are 'a one-time assessment and generally apply only to the increment in land value resulting from the public investment' (Walters, 2012, p. 6). A betterment tax often ranges from 30 to 60% of the value increment. In this case, a betterment tax which is based on expected benefits would be controversial, as the results in this paper suggest an increase in residential property values is likely to be most significant in lower middle-income and upper middle-income neighbourhoods. Furthermore, the impact of a light rail transit system on nearby properties varies over a geographical area, and the magnitude of positive price premiums can vary dramatically. It may be difficult for policy makers to impose a single-value tax if there is also a land value capture policy being considered for implementation.

While the findings are considered robust in estimating the relationship between light rail transit and residential property values, the study could have been made more complete with the incorporation of other data points. Several potentially important independent variables were unavailable, such as building age, number of bathrooms and socio-economic attributes. Other possible refinements would be to more carefully investigate the contextual factors which influence the impact of light rail transit and cause variation in the findings. Therefore, a future study should focus on conducting qualitative surveys, such as semi-structured personal interviews with the local residents within the catchment area (see for instance, Forouhar & Hasankhani, 2018). It must be noted that the primary limitation of a cross-sectional dataset (such as in this paper), is that because the exposure and outcome are simultaneously estimated, there is generally no evidence of a temporal relationship between exposure and outcome (Solem, 2015). Considering this limitation with cross-sectional data, a future study may employ panel data to capture the impact of a light rail transit system on residential property values. Finally, the impact of other types of property, particularly low-cost housing such as flats and apartments, should be estimated.

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Appendix A. Supplementary data

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