INTERNATIONAL JOURNAL OF ACADEMIC RESEARCH IN BUSINESS & SOCIAL SCIENCES
Vol 15, Issue 2, (2025) E-ISSN: 2222-6990

Assessing Urban Land Use Change through Geographical Weighted Regression: Implications for Sustainable Environmental Planning

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To Link this Article: http://dx.doi.org/10.6007/IJARBSS/v15-i2/24440 DOI:10.6007/IJARBSS/v15-i2/24440
Published Date: 03 February 2025

Abstract
Urbanization significantly impacts land use patterns and environmental sustainability. This study uses Geographically Weighted Regression (GWR) to assess urban land use change in a metropolitan area, employing spatially explicit data and GWR modeling techniques to identify local factors influencing land use dynamics. The GWR 4.0 software was utilized for model evaluation and analysis processing, while ArcGIS 10.8 was used for spatial analysis and mapping. Goodness-of-fit criteria were applied to assess the GWR model's performance. The analysis showed improvements in model fit: the Akaike Information Criterion (AICc) decreased from 1509.10 to 1297.31, the Bayesian Information Criterion (BIC) dropped from 1525.77 to 721.24, and the R-squared increased from 0.01 to 0.23, indicating a better fit for localized measurements. The findings reveal that proximity to Mass Rapid Transit (MRT) stations is a significant factor influencing land use changes in the study area. This highlights the need for localized planning strategies that address urban challenges and support sustainable development.
Keywords: Urban land use change, Geographical Weighted Regression (GWR), Sustainable Environmental Planning, Spatial Analysis, Urban Development

Introduction
Urban land use change is a critical phenomenon that reflects the dynamic relationship between human activity and the environment. As cities expand, the demand for land increases, often resulting in significant alterations in land use patterns. These changes, driven by factors such as population growth, economic development, and infrastructural expansion, pose substantial challenges to sustainable urban development worldwide. In particular, urbanization leads to environmental degradation, loss of biodiversity, and increased carbon emissions, making it crucial to address these issues through effective urban planning (UN-

Habitat, 2022). The importance of studying urban land use change lies in its direct impact on the environment and urban sustainability. Understanding the drivers and consequences of these changes allows policymakers, urban planners, and other stakeholders to make informed decisions that balance growth with environmental preservation. This research is particularly significant for regions experiencing rapid urbanization, such as Asia, where cities like Jakarta, Bangkok, and Shanghai are undergoing dramatic shifts in land use (Shen et al., 2019). These urban centers face mounting pressures from population influxes, economic activities, and infrastructural demands, resulting in urban sprawl, environmental strain, and increased vulnerability to climate change. Consequently, sustainable urban planning in these cities has become an urgent priority.

Malaysia, as part of this trend, faces similar challenges with its rapid economic growth and urban expansion. Kuala Lumpur, the capital city, exemplifies these dynamics, with significant land use changes driven by infrastructural developments such as the Mass Rapid Transit (MRT) system. While this growth contributes to the nation's economic progress, it also brings environmental issues such as traffic congestion, pollution, and the loss of green spaces (Tan et al., 2021). Sustainable environmental planning in Kuala Lumpur is crucial to ensuring that future growth does not compromise the city's environmental integrity. The studies by Man and Majid (2024), Man et al. (2024a), Man et al. (2024b), and Man et al. (2024c) provide an in-depth analysis of urban landscape changes and land use patterns in the Klang Valley, with a specific focus on the influence of the Mass Rapid Transit (MRT) system's construction from 2010 to 2020. These papers explore how the development of the MRT has reshaped urban land use, driving urban expansion and significantly altering population density, particularly in areas surrounding MRT stations. Through case studies such as Damansara, and Kuala Lumpur, the research underscores the transformative role of MRT infrastructure in facilitating urbanization, fostering economic growth, and reshaping the social fabric of the region.

Geographically Weighted Regression (GWR) has emerged as an essential tool in urban studies for understanding spatially varying relationships between land use changes and their driving factors. Unlike traditional regression models, which apply uniform relationships across study areas, GWR allows for a more localized analysis, making it particularly valuable in cities with diverse spatial dynamics. By applying GWR to assess urban land use change in Kuala Lumpur, this study aims to provide deeper insights into the region's urbanization trends and inform more effective, context-specific urban planning strategies. The findings offer valuable insights into the broader implications of MRT development for urban planning and the evolving dynamics of metropolitan areas. This highlights the need for advanced spatial analysis techniques, such as Geographically Weighted Regression (GWR), which can better capture the complexities and local variations in land use change (Ding, 2022).

This research is not only relevant to policymakers in Malaysia but also offers lessons for rapidly urbanizing cities globally. Through this study, we aim to bridge the gap between theoretical urban planning concepts and practical, localized applications that can address the challenges posed by rapid urbanization. By uncovering localized patterns in land use changes and their underlying causes, this research will help create a more nuanced understanding of urban development processes, contributing to the advancement of sustainable urban planning practices.

Materials and Methods

Cheras, located in the south-eastern part of Kuala Lumpur, Malaysia, is a rapidly urbanizing suburb, known for its strategic importance within the Klang Valley region. The Bandar Tun Hussein Onn station, a key part of the Sungai Buloh–Kajang MRT line, serves as a significant transit point, driving land use changes and increased real estate development (Ng et al., 2018). Demographically, Cheras is diverse, with a population that includes a mix of ethnic groups and a significant proportion of young working adults. The area is well-connected by major roads and public transport, contributing to its appeal as a residential and commercial hub (Department of Statistics Malaysia, 2020). Physically, Cheras features a mix of flat and hilly terrains, with green spaces like Bukit Permai and Bukit Sungai Putih offering recreational opportunities. Rapid urbanization has led to challenges such as deforestation and loss of green spaces, highlighting the need for sustainable urban planning (Tan & Abdul Rahman, 2019). The area is well-equipped with infrastructure, including healthcare, education, and recreational amenities, making it a desirable location for residents and a focal point for urban development (Loh & Hamid, 2020). Figure 1 below illustrates the geographical location of Cheras, specifically highlighting the area surrounding the Bandar Tun Hussein Onn station. The map delineates key features such as major roads, the MRT line, residential areas, commercial zones, and green spaces within the study area. The positioning of the Bandar Tun Hussein Onn station is marked, showing its strategic location within the broader context of Kuala Lumpur's urban landscape.

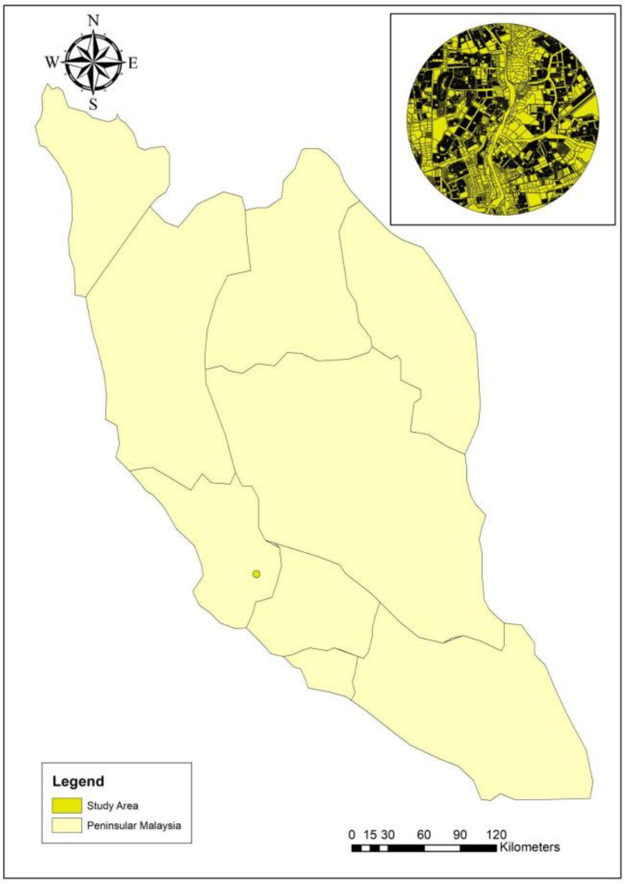

Figure 1: Study area; MRT station Bandar Tun Hussein Onn, Cheras, Kuala Lumpur, Malaysia

Land use data for 2022 were obtained from iPlan Malaysia. Land use types in the database were classified into 10 categories by integrating: residential, transportation, industrial, agriculture, forest, water bodies, recreational land, and so on. All land use classes were visualized in the ArcGIS software. The distance of every location from the MRT station Bandar Tun Hussein On was calculated. Thus, the relationship between land use patterns and distance from the station was established. The GWR model results from the ArcGIS were then used for further analysis.

Geographically Weighted Regression (GWR) is a spatial analysis technique that has gained prominence in urban studies due to its ability to model spatially varying relationships between variables. Unlike traditional regression models, which assume a uniform relationship across the study area, GWR allows for the estimation of local regression parameters, providing a more detailed understanding of the spatial dynamics at play (Fotheringham et al., 2002). The application of GWR in urban studies has yielded valuable insights into various aspects of urbanization and land use change. For example, Tu and Xia (2008) used GWR to examine the impact of transportation infrastructure on property values in Beijing. The study found that the relationship between proximity to transportation networks and property values varied significantly across the city, highlighting the need for localized planning interventions. In the context of environmental planning, GWR has been used to assess the spatial variations in environmental impacts associated with urban land use change. For instance, Hu et al. (2019) applied GWR to analyze the spatially varying effects of land use change on air quality in Shanghai. The study revealed that the impact of land use change on air quality was not uniform across the city, with some areas experiencing more severe degradation than others.

The geographically weighted regression (GWR) model allows parameters to be estimated by a multiple regression model. It is an extension of the ordinary least squares (OLS) regression model (Fotheringham et al., 2002) ignoring the coordinates' observations, Geographically Weighted Regression (GWR) can produce a continuous parameter surface at each local observation to represent spatial variations. This research aims to explore the spatial impact of MRT operations on land use patterns through GWR analysis to align with real-world scenarios. In assessing GWR's benefits in spatial analysis, we compare the accuracy of two regression models. GWR connects variables with localized regression coefficients, utilizing kernel regression to enable varying relationships at different spatial locations (Pasculli et al., 2014).
GWR model can be expressed as:

$$y_i = \beta_o(\mu_i, v_i) + \sum_{i=1}^{k} \beta(\mu_i, v_i)\, \chi_{ij} + \varepsilon_i \quad (1)$$

In this context, y_i represents the dependent variable indicating land use type, the parameters at a specific location i, while μ_i and v_i represent the spatial coordinates for each location i. The term $\beta_0(\mu_i v_i)$ denotes the intercept coefficient specific to location i, and χ_{ij} signifies the value of the explanatory variable j at location i. The coefficient $\beta_i(\mu_i v_i)$ represents the regression coefficient for the ith explanatory variable within the local context. Also, k denotes the quantity of independent variables, while ε_i represents the specific random error term for location i. All observations close to the sampling sites were weighted using a distance decay function in GWR, with the assumption that observations nearer to the sampling sites exert a stronger influence on local estimations (Tu & Xia, 2008). This research employed the adaptive bi-square nearest neighbour formulation as the weight function in the GWR, considering the scattered arrangement of data points throughout the study region. Optimal bandwidths were determined through AICc minimization to improve model performance (Hurvich et al., 1998). The equation defines the kernel shape.

$$\omega ij = \{[1-(dji/hj)2]2\} \text{ otherwise } dji < hj \quad (2)$$

Where,

dji = The distance between observation j and i,
ωij is the weight of observation j for observation i,
hj is the kernel bandwidth which stands for the nth nearest neighbour distance from j.

In the GWR model, a separate regression equation is generated for each observation, allowing for an examination of the spatial relationships between dependent and independent variables to identify spatial non-stationarity (Ding, 2022). The model's regression results include the local parameter estimate, t-test value for local parameter estimates, local R2 value, and local residual value. The local parameter estimate helps analyze positive or negative variable relationships, the local R2 value indicates model fitting optimization t-test value assesses the significance of sampling points, and the local residual calculates the model's spatial autocorrelation.

Results and Discussion

The study area was segmented into 10 categories based on dominant land use types, such as, residential, industrial, recreational area, forest, commercial, infrastructure and utility, agricultural, transportation, institution and facilities, and finally water bodies (see Figure 1). Distance from the MRT station to every location was calculated and overlapped in the ArcGIS software. The data obtained from the software ArcGIS were then processed in the software GWR 4.0.

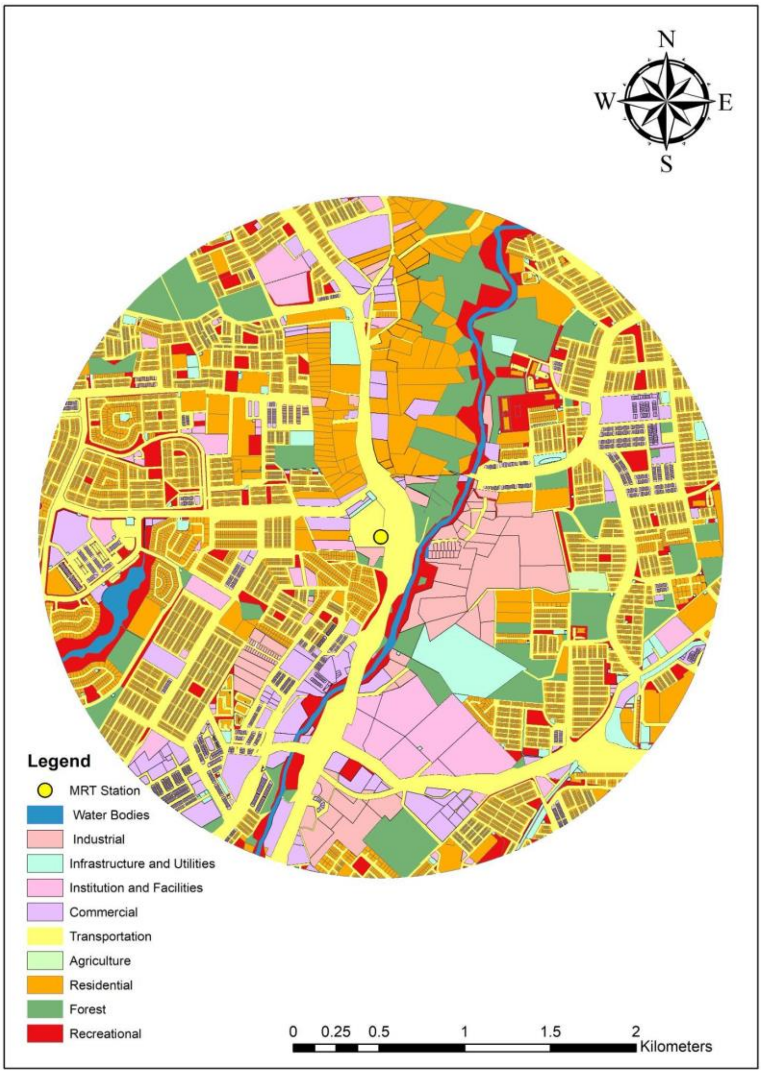

Figure 1 Land Use Map around MRT station Bandar Tun Hussein On

Geographical Weighted Regression is used to analyse the relationship between land use change and explanatory variables "Distance From The Station" within the research area. The GWR framework enables the calculation of localized regression coefficients that change geographically depending on the nearby explanatory variables' proximity and impact. To the reliability of the findings and pinpoint significant spatial clusters of land use change drivers, model diagnostics including spatial autocorrelation and coefficient maps are employed.

The evaluations were calculated using the GWR model in GWR 4.0 software which provides four goodness-of-fit criteria. From the value provided, it shows that the AICc has decreased from 1509.10 to 1297.31. BIC also decreased from 1525.77 to 721.24. While R Square increased from 0.01 to 0.23. Adjusted R Square also increased from 0.0052 to 0.22. These values reveal that GWR is the best model. In general, the local R2 and AICc values of GWR were computed to assess model performance (Hurvich et al., 1998). An increase in the local R2 suggests a strong explanatory power of the independent variables on the dependent variable (Ding, 2022). Additionally, the AICc value was used to evaluate the accuracy and complexity of the regression model, with a lower AICc indicating better predictive capability. This study revealed a significant enhancement in the performance of the GWR model compared to the OLS model. The local R2 values of the GWR models were consistently higher than those of the OLS models, indicating a marked improvement in the models' ability to explain spatial variance in the independent variables. AICc serves as a crucial parameter for evaluating the accuracy and precision of regression models, allowing for comparisons between different model performances.

Table 1
Comparison of OLS Model and GWR Model diagnostics

Criteria	OLS	GWR	Difference
AICc	1509.1	1297.31	- 211.79
BIC/MDL	1525.77	721.24	- 804.53
R Square	0.01	0.23	+ 0.22
Adjusted R Square	0.0052	0.23	+ 0.21

Table 1 shows the comparison between the global regression model and the Geographically Weighted Regression (GWR) model revealing the superior performance of the GWR model in capturing spatial variations within the data. The Akaike Information Criterion corrected (AICc) shows a significant improvement with the GWR model, which has a much lower value of 1297.31 compared to 1509.10 for the global regression model. This difference of −211.79-211.79−211.79 indicates that the GWR model provides a better fit to the data. Similarly, the Bayesian Information Criterion/Minimum Description Length (BIC/MDL) shows a dramatic reduction in the GWR model, with a value of 721.24 compared to 1525.77 for the global model, reflecting a difference of −804.53-804.53−804.53. This suggests that the GWR model more effectively balances model complexity and goodness-of-fit. Additionally, the R-squared (R^2) value shows an improvement in the GWR model, increasing from 0.01 in the global regression model to 0.22, indicating a modest enhancement in the model's explanatory power. The Adjusted R-squared further highlights the GWR model's superiority, with a significant increase from 0.0052 in the global model to 0.22 in the GWR model, a difference of +0.2148. This indicates that the GWR model better accounts for the variability in the data while adjusting for the number of predictors. By analysing AICc and local R2, the study revealed a significant advantage of the GWR model over the OLS model, ensuring better accuracy. Overall, these results demonstrate that the GWR model significantly outperforms the global regression model, providing a more accurate and nuanced understanding of the spatial dynamics within the data.

Land use indicators exhibit both positive and negative associations with “Distance from MRT station” parameters. Some locations showing the positive value of parameters mean that the land use of that area was positively influenced by the MRT station location. As illustrated in Figure 2, some locations show a negative value of parameters, suggesting that the land use of that location hurts the MRT station. The relationship between the percentage land use type and “Distance from the MRT station” had shown an obvious spatial non-stationarity according to GWR model results, which suggests that:

Table 2
Coefficients Values for variable Distance to the Station

Variable	Coefficient			
	Mean	STD	Min	Max
Distance from MRT station	0.000084	0.0018	-0.006	0.008

Meanwhile, Table 2 describes the local parameter coefficient statistics of the factor that impacts the land use pattern, and distance to the station. Distance to the station range is from -0.006 to 0.008 with a mean of 0.000084. The results from the Geographically Weighted Regression (GWR) analysis for the variable "Distance to the Station" reveal notable spatial variability in its impact on the dependent variable. The mean coefficient across all analyzed locations is 0.000084, indicating that, on average, the distance to the station has a minimal positive effect on the dependent variable. However, this average effect is not consistent across the entire study area. The standard deviation (STD) of the coefficient is 0.0018, suggesting that the relationship between distance to the station and the dependent variable differs significantly depending on the location. This variability is further illustrated by the minimum and maximum coefficient values. The minimum coefficient observed is 0.006, showing that in some areas, increasing the distance to the station is associated with a negative impact on the dependent variable. In contrast, the maximum coefficient is 0.008, indicating that in other areas, greater distance from the station positively influences the dependent variable. These results highlight the importance of considering local spatial variations when analyzing the effects of distance to the station, as the impact can differ widely across different regions. The GWR model effectively captures these variations, providing a more nuanced understanding of the spatial dynamics at play.

Discussion

Figure 2 illustrates the coefficient map of the influencing factors to the land use change in the study area. The results indicate a spatial variation relationship between land use pattern and the land use change influencing factors in the study area. Land use change is a complex phenomenon. Its occurrence is due to many factors that are constantly associated with each other. It is crucial to identify the factors that influence the land use patterns. These estimated parameter values were calculated in the ArcGIS software. Negative values for parameters value indicate a negative influence on the dependent variable, whereas a positive sign shows a significant influence on the occurrences of parameters towards the dependent variable. Distance to Station as shown in Figure 1 conveys various values from -0.0057 to 0.0079 with positive values and negative values scattered around the study area. This shows that distance to the station does influence the land use pattern at certain locations in the study area as depicted in Figure 1.

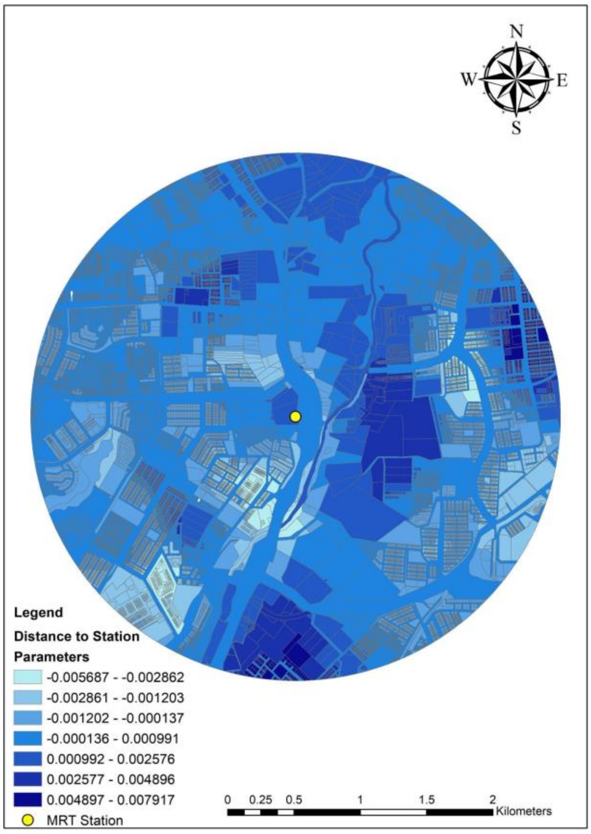

Figure 2 Estimated parameter values for land use change factor: Distance from the station

Local R2 denotes the ideal alignment of independent and dependent. A greater R2 signifies that an independent variable can more effectively explain the variance in a dependent variable. However, the importance of the measurement equation outweighs statistical significance. Even a relatively low fit in a GWR model can accurately depict relationships, provided they are meaningful in environmental studies.

The local R2 values of the GWR model showed significant spatial variability, ranging from 0 to 0.64. Strong correlations and higher local R2 values were seen in regions near the MRT, and lower values were noted in areas far from the MRT. The average local R2 of all GWR models in this study is 0.23, suggesting that "distance to MRT station" can only explain 23% of the impact on land use patterns in the study area. These variations indicate that the explanatory capacity regarding land use pattern is not solely influenced by population and income status, but also by the number of associated "distance to MRT station" parameters considered. GWR models enable the examination of spatially varying effects from land use to "distance to station" parameters through local parameter estimates and local R2 results.

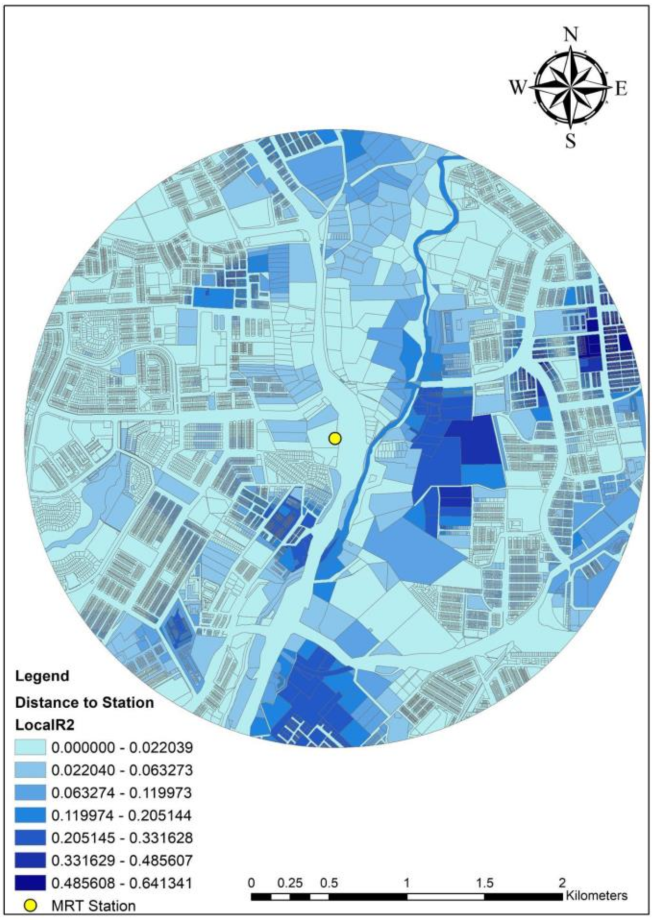

Figure 3 Spatial distribution of GWR-estimated parameters: Local R2

The findings from studies employing GWR have important implications for sustainable environmental planning. The spatial variability revealed by GWR analysis suggests that one-size-fits-all planning approaches may be inadequate for addressing the complex challenges associated with urban land use change. Instead, localized strategies that consider the unique spatial dynamics of different areas are necessary to achieve sustainable urban development (Miller & Wentz, 2003). In Malaysia, the use of GWR in assessing urban land use change offers valuable insights for policymakers and urban planners. By identifying areas where land use changes are most pronounced, and understanding the factors driving these changes, planners can develop targeted interventions to mitigate negative environmental impacts. For example, in Kuala Lumpur, areas identified as particularly sensitive to urbanization pressures could be prioritized for green space preservation, traffic management, and sustainable infrastructure development (Lim & Nor, 2020). Moreover, the integration of GWR into environmental planning frameworks can enhance the effectiveness of policy interventions by providing a more accurate understanding of the spatial relationships between urbanization and environmental outcomes. This approach aligns with the goals of sustainable development, which emphasize the need for context-specific solutions that balance economic growth with environmental stewardship (UN-Habitat, 2016).

Conclusion

The findings of this study demonstrate that the Geographically Weighted Regression (GWR) model outperforms the Ordinary Least Squares (OLS) model in explaining urban land use change. The GWR model shows significantly higher values for R² (0.23), adjusted R² (0.23), and a lower Akaike Information Criterion corrected (AICc) value (1297.31) compared to the OLS model's R^2 (0.01), adjusted R^2 (0.0052), and AICc value (1509.10). These statistical indicators indicate that GWR is more effective in capturing the spatial non-stationary characteristics of land use patterns and their influencing factors.

By applying GWR to assess urban land use change, this study provides valuable insights into the spatial dynamics of urban development, particularly how the proximity to the Mass Rapid Transit (MRT) station influences local land use patterns. The findings underscore the importance of localized planning strategies that account for spatial variations in land use drivers, which can improve urban policies and contribute to the development of more resilient and liveable cities.

However, this study has certain limitations. It primarily examines 'distance to MRT' as a single factor influencing land use patterns. Future research should broaden this analysis by incorporating additional explanatory variables and exploring the complex interactions between various spatial factors affecting land use. A more comprehensive understanding of these relationships will enable urban planners and policymakers to develop more effective and context-specific urban development strategies. Additionally, future studies should integrate other spatial dynamics, such as land accessibility, socio-economic factors, and infrastructure development, to establish a more holistic approach to urban planning.

Acknowledgment
This work was supported by the Geran Universiti Penyelidikan (GUP) grant number GUP-2023-025. The authors acknowledge the collaboration and co-research, as well as the materials provided by iPlan Malaysia and the UKM Library for this project.

Declaration of Competing Interest
The authors declare the following potential competing interests. All authors report financial support from Universiti Kebangsaan Malaysia. All other authors declare that they have no known competing financial interests or personal relationships that could have influenced the work reported in this paper.

Data Availability
No data was used for the research described in the article.

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