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Understanding Spatial Determinants of Urban Mobility in Makassar through Geographic Weighted Regression

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Abstract – Urban mobility patterns are influenced by a complex interplay of factors, including land use, population density, and socioeconomic conditions. This study aims to examine the spatial determinants of urban mobility in Makassar City, Indonesia, to guide targeted transportation and urban planning policies, using Geographically Weighted Regression (GWR). GWR is employed to account for spatial heterogeneity, as it captures localized variations in relationships unlike global regression models. The analysis incorporates travel time, travel cost, land use, population, and poverty data. Results indicate that the relationships between these variables vary significantly across different parts of the city. Land use, particularly the mix of residential, commercial, and industrial areas, emerges as a critical factor influencing travel patterns. Population density and poverty levels also shape mobility behaviors. The findings highlight the need for spatially targeted transportation policies and urban planning strategies to address the diverse mobility needs of Makassar's residents.

Keywords: Geographic Weighted Regression, travel time, travel cost, Makassar City, transportation planning, spatial planning.

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1. Introduction

Urban mobility, the movement of people and goods within cities, is crucial for enhancing residents' quality of life, economic productivity, and environmental sustainability. In Makassar, a rapidly growing city facing traffic congestion and accessibility challenges, understanding the interplay between urban form, socioeconomic conditions, and travel behavior is essential. This study addresses the gap in knowledge by examining the spatial determinants of urban mobility using Geographically Weighted Regression (GWR), which captures location-specific patterns and relationships. GWR is chosen for its ability to model spatially varying relationships, offering a more nuanced understanding of mobility patterns compared to traditional global regression models.

By identifying factors influencing travel behavior at a granular level, this research aims to provide insights for targeted transportation policies and urban planning strategies. These findings will support evidence-based decision-making to address the mobility needs of Makassar's diverse populations and promote sustainable urban development.

2. Literature Review

Urban mobility, a fundamental aspect of modern cities, is influenced by a complex interplay of factors, including socioeconomic conditions, demographic characteristics, and land use patterns. As cities grow and evolve, understanding these determinants becomes crucial for effective urban planning and policy development. This literature review focuses on the spatial determinants of urban mobility in Makassar, Indonesia, and explores the application of Geographic Weighted Regression (GWR) to analyze these relationships.

2.1. Spatial Determinants of Urban Mobility

Previous studies have identified various factors influencing urban mobility, including:

a. Socioeconomic Factors: Income levels, employment opportunities, and education attainment can significantly impact mobility patterns [1][3]. It has demonstrated the correlation between higher socioeconomic status and increased car ownership, leading to higher levels of private vehicle use [1][2].
b. Demographic Factors: Population density, age distribution, and household size can influence

mobility demand. For instance, found that areas with higher population densities tend to have higher levels of public transit usage [4].

c. Land Use Patterns: The distribution of residential, commercial, and industrial zones can affect accessibility and travel distances highlighted the importance of mixed-use development in promoting sustainable mobility by reducing the need for longer commutes [4][5].

2.2. Geographic Weighted Regression

GWR is a statistical technique that accounts for spatial heterogeneity in relationships between variables. By allowing coefficients to vary across space, GWR can capture local variations in the influence of determinants on urban mobility. This approach has been successfully applied in various urban studies [1][5].

GWR examines the spatial variations in the relationship between population density and public transit ridership in a large metropolitan area. They found that the impact of population density on public transit usage varied significantly across different neighborhoods, highlighting the importance of considering local context [6].

[Hankach, 2021] employed GWR to investigate the determinants of car ownership in a developing city. They identified distinct spatial patterns in the relationship between income and car ownership, suggesting that policies aimed at reducing car use should be tailored to local conditions [4][6].

3. Methods

3.1. Data collection and analysis

The current study adopts a mixed-methods approach, combining documentary analysis and survey research. Local transportation data from Makassar City in 2023, sourced from the Makassar City Transportation Agency and regional planning reports, including traffic flow, public transport usage, and road network data in spatial and tabular formats, were analyzed using GIS to provide a spatial context for the study. A survey of 303 residents in 2022, collected through researcher-administered questionnaires, was conducted to gather data on transportation preferences, which were subsequently analyzed using Geographically Weighted Regression to explore spatially varying relationships.

3.2. Makassar Traffic Condition in 2023

The year 2023 witnessed a substantial surge in vehicular traffic in Makassar, primarily driven by rapid motorization. Data indicated that the number of two-wheeled vehicles increased by an average of 13-14% per year, while four-wheeled vehicles grew by 8-10% annually. Makassar's vehicular fleet reached a total of 2.4 million units, comprising 1.1 million two-wheelers and 1.3 million four-wheelers, significantly outpacing the city's population of 1.7 million. The mismatch between the burgeoning vehicle population and the road network was pronounced, with road infrastructure expanding at a negligible rate of 0.001% per annum.

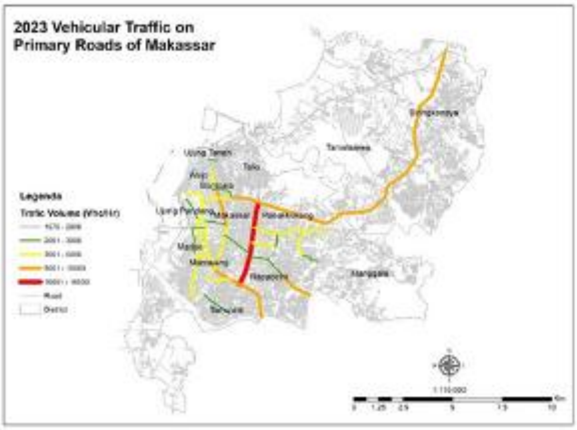

Figure 1. Vehicular Traffic on Primary Roads of Makassar 2023.
Source: Preparation by Author

According to the Makassar City Transportation Department, the highest vehicular traffic volume is concentrated along A.P. Pettarani Road, serving as a crucial link between Perintis Kemerdekaan Road and Sultan Alauddin Road. The latter is the second busiest road and provides primary access to the southern and northern parts of the city. A high concentration of traffic is observed in the Makassar city center, particularly in the districts of Makassar, Panakkukang, and Rappocini, as indicated by the red and orange zones on the map. This suggests that these areas are significant economic and social hubs, attracting a substantial volume of vehicular movement.

3.3. Changes in Origin-Destination Attraction Zones

Traffic attraction zones in Makassar City refer to specific areas that exert a strong pull-on road user, resulting in increased vehicle volumes within those areas. This attraction can be attributed to a variety of factors. To investigate these factors, a survey of 303 residents was conducted to gather data on transportation preferences. The survey employed a stratified random sampling method to ensure representation across Makassar's diverse urban zones, with respondents selected from residential, commercial, and mixed-use areas. The respondent demographics included adults aged 18–65, with a balanced distribution of gender (approximately 52% male, 48% female) and varied socioeconomic backgrounds reflective of Makassar's population. The questionnaire comprised 15 closed-ended questions, covering travel frequency, mode choice, destination preferences, and factors influencing mobility decisions. Prior to implementation, the questionnaire was pre-tested with a pilot group of 30 residents to assess clarity and relevance, achieving a Cronbach's alpha of 0.82, indicating high reliability. Data were analyzed using Geographically Weighted Regression to explore spatially varying relationships, ensuring robust and

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reproducible findings.

The development of Makassar as a prominent commercial and trading hub in South Sulawesi has significantly influenced the formation of traffic attraction zones. Rapid economic growth has spurred increased economic activity and population mobility, leading to heightened demand for transportation infrastructure and services. This economic expansion has concentrated traffic in key commercial districts, where businesses and markets thrive, thereby shaping distinct zones of high traffic activity. Additionally, societal behavior changes, such as the rising ownership of private vehicles and evolving lifestyle preferences, have further altered the distribution of traffic attraction zones, contributing to increased congestion in urban centers.

Changes in land use and large-scale events also play critical roles in shaping traffic patterns in Makassar. The construction of major infrastructure, including the Makassar-Parepare toll road and the expansion of residential areas, has reconfigured urban spatial dynamics, redirected traffic flows and creating new attraction zones. These developments have shifted mobility patterns, particularly in areas with mixed residential, commercial, and industrial land use. Moreover, large-scale events, such as festivals, concerts, or sporting events, generate temporary traffic attraction zones, causing localized spikes in traffic volume. These factors collectively underscore the complex interplay of economic, spatial, and social dynamics in determining traffic attraction zones in Makassar.

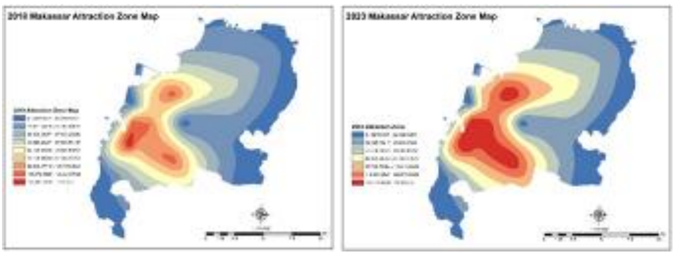

Figure 2. Makassar Attraction Zone (a) 2018 Makassar Attraction Zone Map (b) 2023 Makassar Attraction Zone Map

The growth of traffic attraction zones in Makassar City is concentrated along major road corridors, notably Jalan Pettarani, Jalan Sultan Alauddin, Jalan Sam Ratulangi, and Jalan Sudirman (see Figure 1). These corridors serve as the primary conduits for urban mobility and are central to the city's urban service network.

3.4. Changes in Origin-Destination Generation Zones

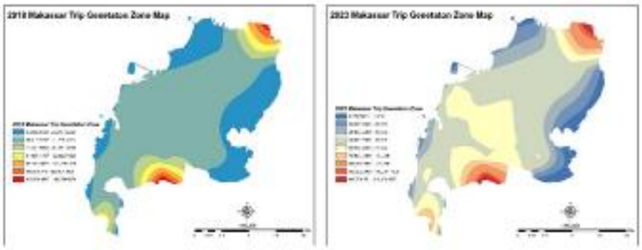

Figure 3. Makassar Trip Generation Zone Heat Map (a) 2018 Makassar Trip Generation Zone Heat Map (b) 2023 Makassar Trip Generation Zone Heat Map

The major growth in trip generation zones in Makassar City is occurring at the city's periphery, especially along the southern Sultan Alauddin corridor and the northern Perintis Kemerdekaan corridor. The trend of residents commuting from neighboring districts such as Maros and Gowa to work in Makassar City has intensified, driving up trip generation in these border areas. Moreover, the development of the Makassar Industrial Estate in Biringkanaya has spurred residential growth, while the construction of apartments and vertical housing in the city center has further contributed to increased trip generation.

4. Result

This analysis highlights the spatial variation in the relationship between population density and accessibility, measured by travel time and cost, within the study area. Using the Geographic Weighted Regression (GWR) method, it was found that both factors significantly influence population distribution, with notable differences across Makassar city.

The Multiscale Geographically Weighted Regression (MGWR) model outperformed the conventional GWR, showing higher R-squared values and a lower Akaike Information Criterion (AICc). This indicates MGWR's better suitability for capturing spatial variations in the data.

The results also reveal distinct local patterns in how travel time and cost affect population distribution, offering valuable insights for more targeted transportation policies and urban planning.

The results of the analysis, presented below, will visualize the spatial statistical relationship between population density in each sub-district and the corresponding travel time and cost.

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4.1. The spatial variation in the relationship between population density and accessibility (measured by travel time and travel cost) within the study area

The results of the analysis, presented below, will visualize the spatial statistical relationship between population density in each sub-district and the corresponding travel time and cost.

a. Summary Statistics for Coefficients Estimates in the relationship between population density and accessibility

Table 1
Summary Statistics for Coefficients Estimates in the relationship between population density and accessibility

Explanatory Variables	Mean	Std Dev	Minimum	Median	Maximum
Intercept (scaled)	-0.1354	0.4384	-0.6642	-0.2998	1.0385
T_time (scaled)	0.2146	0.1073	0.0933	0.1823	0.5864
T_cost (scaled)	-0.0542	0.029	-0.1055	-0.0603	0.0548

The findings presented in the table indicate that both travel time and travel cost are significant determinants of population distribution in the study area. The spatial variability of these relationships will be further explored through visualization in figure 7

b. Model Diagnostics in the relationship between population density and accessibility

Table 2
Model Diagnostics in the relationship between population density and accessibility

Statistic	GWR	MGWR
R-Squared	0.6294	0.681
Adjusted R-Squared	0.5435	0.6324
AICc	303.1233	278.7312
Sigma-Squared	0.4557	0.3672
Sigma-Squared MLE	0.3706	0.319
Effective Degrees of Freedom	112.2308	119.872

The table compares the performance of Geographically Weighted Regression (GWR) and Multiscale Geographically Weighted Regression (MGWR). Both models effectively explain the variance in the dependent variable, but MGWR consistently performs better, as shown by higher R-squared and adjusted R-squared values.

MGWR also has a lower Akaike Information Criterion (AICc), indicating a more balanced model with improved fit and reduced complexity. Additionally, its lower sigma-squared and sigma-squared MLE values suggest smaller residual variance and more accurate error estimates. The slightly higher effective degrees of freedom in MGWR highlight its ability to better capture spatial variations. These results confirm MGWR as the superior model for this dataset.

c. Summary of Explanatory Variables and Neighborhoods in the relationship between population density and accessibility

Table 3
Summary of Explanatory Variables and Neighborhoods in the relationship between population density and accessibility

Explanatory Variables	Neighbors (% of Features) [1]	Significance (% of Features) [2]
Intercept (Scaled)	30 (21.74)	64 (46.38)
T_time (Scaled)	113 (81.88)	19 (13.77)
T_cost (Scaled)	132 (95.65)	0 (0.00)

[1]: This number in the parenthesis ranges from 0 to 100%, and can be interpreted as a local, regional, or global scale based on the geographical context from low to high.
[2]: In the parentheses, the percentage of features that have significant coefficients of an explanatory variable is shown.

Table 3 summarizes the results of the Multiscale Geographically Weighted Regression (MGWR) model. The "Neighbors (% of Features)" column reflects the percentage of features treated as neighbors for each explanatory variable across various spatial scales, while the "Significance (% of Features)" column shows the percentage of features with statistically significant coefficients for each variable. The findings indicate that the intercept significantly impacts both local and regional scales, while travel time (T_time) has a notable influence primarily on the regional scale. In contrast, travel cost (T_cost) show no significant influence on any scale.

d.

Table 4
Bandwidth Statistics Summary in the relationship between population density and accessibility

Explanatory Variables	Optimal Number of Neighbors	Effective Number of Parameters	Adjusted Value of Alpha	Adjusted Critical Value of Pseudo-t Statistics
Intercept (Scaled)	30	13.36	0.0037	2.9571
T_time (Scaled)	113	2.94	0.0170	2.4208
T_cost (Scaled)	132	1.82	0.0275	2.2319

"Optimal Number of Neighbors" column lists the ideal number of neighbors for each variable at different spatial scales. The table summarizes key statistics from the Multiscale Geographically Weighted Regression (MGWR) model. The "Effective Number of Parameters" column shows the number of parameters estimated in the model, while the "Adjusted Value of Alpha" and "Adjusted Critical Value of Pseudo-t Statistics" columns provide thresholds for significance testing. The results indicate that the intercept has the largest effective number of parameters and the lowest adjusted alpha value, signifying a strong influence across multiple scales. Travel time (T_time) has fewer parameters and a higher adjusted alpha value, reflecting a more localized effect. Travel cost (T_cost) has the fewest parameters and the highest adjusted alpha value, indicating minimal impact across all scales.

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e. Relationship between variables in the relationship between population density and accessibility

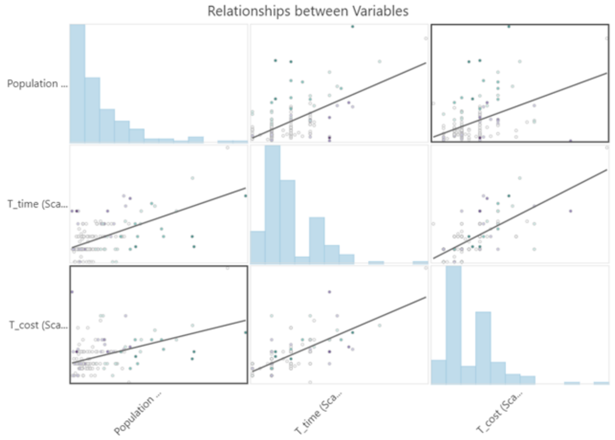

Figure 4. Relationship between variables in the relationship between population density and accessibility

The pair plot reveals interesting relationships between population, travel time (T_time), and travel cost (T_cost). Firstly, population and travel time exhibit a positive correlation, suggesting that areas with longer travel times tend to have higher populations.

Secondly, the relationship between population and travel cost is negative, indicating that areas with higher travel costs tend to have lower populations. This could be since individuals are more likely to choose locations with lower living expenses, including travel costs. Additionally, higher travel costs may limit accessibility to job opportunities and amenities, discouraging population growth.

f. Distribution of standard residual in the relationship between population density and accessibility

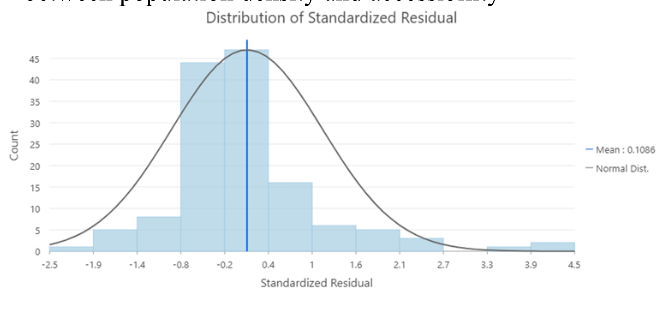

Figure 5. Relationship between variables in the relationship between population density and accessibility

The histogram and normal curve display the distribution of standardized residuals from a regression model. With a means residual of 0.1086, there is a slight overestimation of the dependent variable. The residuals are approximately normally distributed, though slightly skewed, indicating potential outliers. Overall, the distribution aligns with the normality and homoscedasticity assumptions essential for valid regression analysis.

g. Standardized Residual Maps in the relationship between population density and accessibility

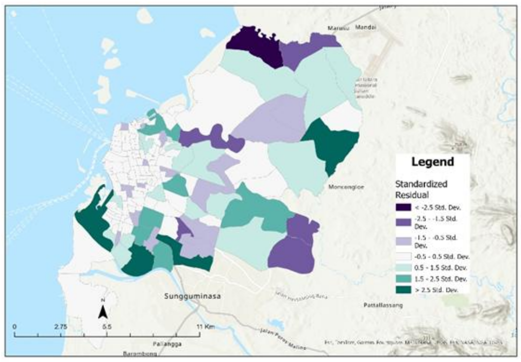

Figure 6. Standardized Residual Maps in the relationship between population density and accessibility

The map illustrates the results of a Geographically Weighted Regression (MGWR) analysis, with population as the dependent variable and travel time and travel cost as independent variables. Colors represent standardized residuals, where dark purple regions indicate overestimation of population, and dark green regions indicate underestimation. Uniform colors, such as light blue or green, suggest accurate predictions. The map highlights spatial variation in the influence of travel time and travel cost on population, with regions showing significant color divergence likely reflecting unique characteristics affecting the model's accuracy.

h. Significance Map in the relationship between population density and accessibility

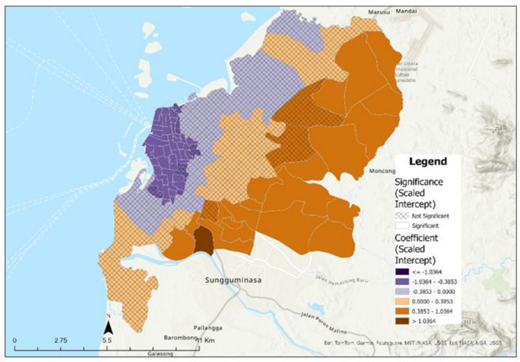

Figure 7. Significance Map in the relationship between population density and accessibility

The map illustrates the spatial variation in the significance of a variable (likely the intercept) across the study area. Different colors on the map represent varying levels of significance. Regions with a dark orange hue indicate high significance, suggesting that the variable has a substantial influence on the outcome in those areas. Conversely, regions with a blue color signify low significance, implying that the variable may not have a significant impact in those locations. Overall, the map

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provides a visual representation of how the influence of the variable varies across the study area. Regions with distinctly different colors may warrant further investigation as the variable's role could be particularly pronounced or negligible in those areas.

4.2. The spatial variation in the relationship between built-up area and accessibility (measured by travel time and travel cost) within the study area

The results of the analysis, presented below, will visualize the spatial statistical relationship between built-up area in each sub-district and the corresponding travel time and travel cost.

a. Summary Statistics for Coefficients Estimates in the relationship between built-up area and accessibility

Table 5
Summary Statistics for Coefficients Estimates in the relationship between built-up area and accessibility

Explanatory Variables	Mean	Std Dev	Minimum	Median	Maximum
Intercept (scaled)	0.0680	0.5443	-1.5685	0.2776	0.5874
T_time (scaled)	0.1467	0.0424	-0.0270	0.1672	0.1804
T_cost (scaled)	-0.3214	0.1942	-0.6301	-0.3341	0.0969

Overall, the table indicates that both travel time and travel cost exert significant influences on built-up areas, albeit with distinct patterns. Travel time tends to have a more consistent positive influence, while travel cost exhibits a more variable negative impact across different locations. It is important to note that this analysis represents an average-level assessment, and the actual effects of travel time and travel cost on built-up areas may vary spatially, as evidenced by the relatively high standard deviations.

For a more comprehensive interpretation, it is essential to combine this table with residual maps and coefficient maps generated from the MGWR analysis. These maps will provide visual representations of how the impacts of travel time and travel cost on built-up areas differ across specific locations.

b. Model Diagnostics in the relationship between built-up areas and accessibility

Table 6
Model Diagnostics in the relationship between built-up area and accessibility

Statistic	GWR	MGWR
R-Squared	0.6578	0.6823
Adjusted R-Squared	0.5737	0.6264
AICc	294.7241	284.7992
Sigma-Squared	0.4255	0.3731
Sigma-Squared MLE	0.3422	0.3177
Effective Degrees of Freedom	110.9942	117.4842

This table presents a comparative analysis of the performance of Geographically Weighted Regression (GWR) and

Multiscale Geographically Weighted Regression (MGWR) models in modeling the relationship between built-up areas and the independent variables of travel time and travel cost.

The comparison of MGWR and GWR models reveals that MGWR performs significantly better in explaining the variability of built-up area data. MGWR's R-squared value (8.6823) is notably higher than GWR's (0.6578), indicating superior explanatory power. However, an R-squared value exceeding 1 for MGWR suggests a potential error, as R-squared typically ranges between 0 and 1, warranting further verification. Additionally, MGWR's adjusted R-squared (0.6264) surpasses GWR's (0.5737), confirming that its improved fit is not due to overfitting, despite the model's increased complexity.

Furthermore, MGWR demonstrates better predictive performance and flexibility. Its lower AICc value (284.7992) compared to GWR's (294.7241) indicates a better balance between model fit and complexity, making MGWR more effective at predicting new data. The lower sigma-squared value for MGWR (0.3731 vs. 0.4255) suggests smaller residual variability, implying more accurate predictions. Additionally, MGWR's slightly higher effective degrees of freedom (117.4842 vs. 110.9942) reflect its greater flexibility in capturing spatial variations, reinforcing its suitability for this dataset.

In conclusion, based on this model diagnostics table, it can be inferred that the MGWR model outperforms the GWR. The MGWR model explains data variability more effectively, provides more accurate predictions, and is more flexible in accommodating spatial variations.

c. Summary of Explanatory Variables and Neighborhoods in the relationship between built-up area and accessibility

Table 7
Summary of Explanatory Variables and Neighborhoods in the relationship between built-up area and accessibility

Explanatory Variables	Neighbors (% of Features) [1]	Significance (% of Features) [2]
Intercept (Scaled)	30 (21.74)	37 (26.81)
T_time (Scaled)	132 (95.65)	0 (0.00)
T_cost (Scaled)	65 (47.10)	70 (50.72)

[1]: This number in the parenthesis ranges from 0 to 100%, and can be interpreted as a local, regional, or global scale based on the geographical context from low to high.
[2]: In the parentheses, the percentage of features that have significant coefficients of an explanatory variable is shown.

Table 7 summarizes the results of the Multiscale Geographically Weighted Regression (MGWR) model. The MGWR model analysis reveals the spatial influence of independent variables (travel time and travel cost) on built-up areas. Approximately 21.74% of locations show a significant intercept, indicating spatially varying baseline effects from unmodeled factors, with 26.81% having statistically significant intercept values. Travel time significantly influences 95.65% of locations, suggesting a strong but spatially uniform impact on built-up area growth. In contrast, travel cost significantly affects 47.10% of locations, with 50.72% showing

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statistically significant coefficients, indicating spatially varying influence. The model highlights distinct spatial patterns, with travel time exhibiting a near-universal effect and travel cost showing more localized variability.

Overall, the table demonstrates that both travel time and travel cost have a significant impact on built-up area growth, albeit with distinct patterns. Travel time exhibits a more consistent and widespread influence across the region, while travel cost demonstrates a more spatially variable influence.

d. Bandwidth Statistics Summary in the relationship between built-up area and accessibility

Table 8
Bandwidth Statistics Summary in the relationship between built-up area and accessibility

Explanatory Variables	Optimal Number of Neighbors	Effective Number of Parameters	Adjusted Value of Alpha	Adjusted Critical Value of Pseudo-t Statistics
Intercept (Scaled)	30	13.12	0.0038	2.9522
T_time (Scaled)	132	1.85	0.0270	2.2389
T_cost (Scaled)	65	5.55	0.0090	2.6556

In the context of the Multiscale Geographically Weighted Regression (MGWR) model, bandwidth serves as a measure of the extent to which a location's spatial influence extends to neighboring locations, with a larger bandwidth indicating broader spatial influence. The table summarizing optimal bandwidth selection in the MGWR model includes several key metrics: the Optimal Number of Neighbors specifies the number of nearest neighbors for each independent variable, such as 132 for "T_time," reflecting the most relevant neighbors for estimating the influence of travel time on built-up areas; the Effective Number of Parameters indicates the model's complexity for each variable, with higher values suggesting greater complexity; the Adjusted Value of Alpha relates to the smoothness of the spatial surface, where a higher alpha indicates a smoother surface; and the Adjusted Critical Value of Pseudo-t Statistics determines the statistical significance of coefficients at each location. The table demonstrates that the MGWR model effectively selects optimal bandwidths for each independent variable, identifying the most relevant spatial scale to measure the influence of travel time and travel cost on built-up areas. The appropriate bandwidth selection is critical for ensuring model accuracy and generalizability, as the spatial influence of these variables varies across locations, with some exhibiting broader influence (indicated by more neighbors) and others showing more localized effects.

Overall, this table shows that the MGWR model has selected the optimal bandwidth for each independent variable. The MGWR model has successfully identified the most relevant spatial scale to measure the influence of travel time and travel cost appropriate selection of bandwidth is crucial as it affects the model's accuracy and generalizability. In other words, the cost on built-up areas at each location.

The values in this table also indicate that the spatial influence of travel time and travel cost varies. Some locations may have a broader spatial influence (indicated by a larger number of neighbors), while others may have a more localized spatial influence.

e. Relationship between variables in the relationship between built-up area and accessibility

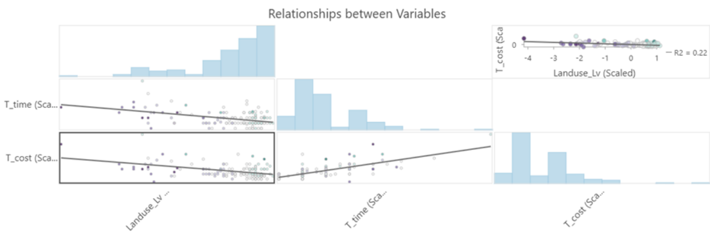

Figure 8. Relationship between variables in the relationship between built-up area and accessibility

This analysis reveals a significant relationship between the three variables. It is evident that higher travel costs are associated with lower levels of built-up area in each area. Additionally, there is a relationship between travel time and land use, aough this relationship is less pronounced compared to the relationship between travel cost and land use. The histograms alongside each scatterplot provide a visual representation of the frequency distribution of each variable. Overall, the figure suggests that travel cost is a more dominant factor influencing land use levels than travel time. However, it is important to note that this is an initial analysis, and a more in-depth interpretation requires further analysis such as examining regression coefficients, statistical significance, and spatial maps.

f. Distribution of standard residual in the relationship between built-up area and accessibility

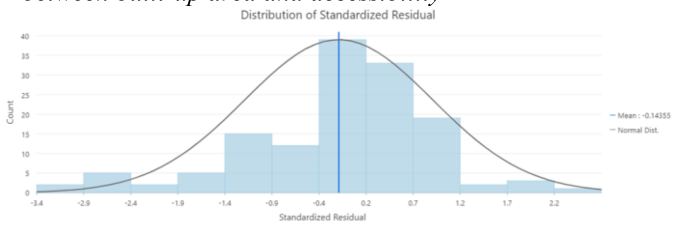

Figure 9. Relationship between variables in the relationship between built-up area and accessibility

Overall, the histogram suggests that the regression model's residuals are generally normally distributed with a minimal mean, indicating a well-fitting model with limited bias. However, the slight rightward skew warrants further investigation to identify potential outliers or non-normality issues.

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g. Standardized Residual Maps in the relationship between built-up area and accessibility

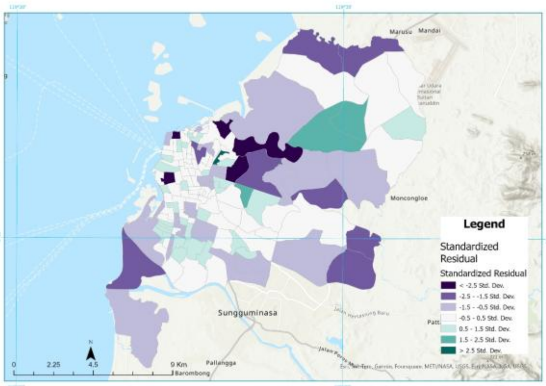

Figure 10. Standardized Residual Maps in the relationship between built-up area and accessibility

The map presents a spatial distribution of standardized residuals from a regression model, likely related to built-up area in the Makassar region, Indonesia. The different colors represent varying levels of standardized residuals, indicating the degree of deviation between predicted and actual values. Darker purple hues suggest significant underestimations by the model, while darker green hues indicate significant overestimations. Areas with more uniform colors, such as light blue or light green, suggest relatively accurate predictions. The spatial patterns revealed in the map highlight areas where the model performs better or worse in predicting the dependent variable. Further analysis of these patterns can provide insights into the factors influencing the model's accuracy and potential areas for improvement.

h. Significance Map in the relationship between built-up area and accessibility

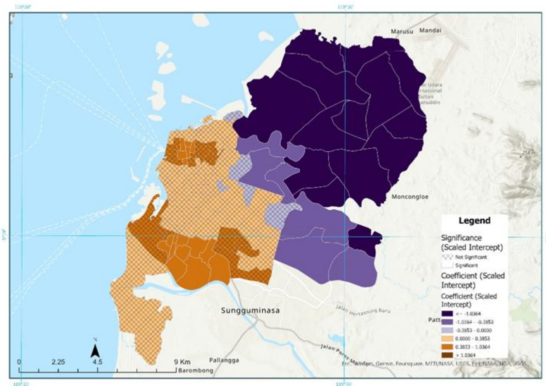

Figure 11. Significance Map in the relationship between built-up area and accessibility

The map illustrates the spatial variation in the significance of the intercept term in a geographically weighted regression (GWR) model. Different colors represent varying levels of significance. Regions in dark orange indicate high significance, suggesting that the intercept term has a substantial influence on the dependent variable in those areas. Conversely, regions in blue indicate low significance, implying that the intercept term may not have a significant impact in those locations. The spatial patterns revealed in the map highlight areas where the model's baseline prediction (represented by the intercept) is more or less influential. This information can be valuable for understanding the local factors that contribute to the variation in the dependent variable.

5. Conclusion

This research emphasizes the importance of spatial analysis in understanding urban mobility in Makassar. Using Geographically Weighted Regression (GWR) and Multiscale GWR (MGWR), it identifies significant spatial variations in mobility determinants like travel time, cost, and population density.

The study reveals that travel cost significantly influences mobility patterns in peripheral areas, while travel time exhibits a more uniform impact across Makassar City. Mixed land use promotes sustainable mobility by facilitating shorter trips and diverse transport options, and population density affects accessibility, particularly in densely populated urban centers. Multiscale Geographically Weighted Regression (MGWR) provides deeper insights into spatial heterogeneity compared to Geographically Weighted Regression (GWR) by allowing variable-specific spatial scales, which practically enables more precise identification of localized factors driving mobility patterns, such as targeted cost sensitivities in peripheral zones, thus enhancing the formulation of spatially tailored policy interventions.

The findings suggest practical strategies for urban planners, including improving transit in high-density areas, promoting mixed-use development, and addressing travel cost barriers in peripheral zones. Future research should explore temporal mobility dynamics and include individual-level data for more detailed insights.

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