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SPATIALLY SIGNIFICANT ANALYSIS OF THE VOLUME WITH SPEED RELATIONSHIP AT SIGNALIZED INTERSECTIONS

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Abstract

In Kediri City, Indonesia this study examines the spatial variations in the correlation between vehicle speed and traffic volume at signalized junctions. Field surveys were conducted during peak-hour periods at eight signalized intersections, with 30 directional approaches used as observation units. The analysis considered four vehicle categories: motorcycles, passenger cars, trucks, and buses. Geographically Weighted Regression (GWR) was utilized to investigate local variation in volume-speed sensiticity, whereas Ordinary Least Squares (OLS) regression served as a global reference model. The results show that higher traffic volume is generally associated with lower vehicle speed, but the strength of this relationship differs by location and vehicle type. Motorcycles have the weakest sensitivity because of their greater maneuverability in mixed traffic. In contrast, trucks and buses show stronger speed reductions due to larger vehicle dimensions, lower acceleration capability, and greater maneuvering-space requirements. Spatially, Alun-Alun and Kemuning intersections show stronger local volume–speed relationships, as indicated by more negative local coefficients and higher Local R^2 values. The ANOVA-based comparison indicates that GWR provides different levels of improvement over the global model, particularly for heavy vehicles. These findings support the need for signalized intersection management that considers both local traffic conditions and vehicle-type characteristics.

Keywords: Geographically Weighted Regression (GWR); Signalized Intersection; Spatial Analysis; Traffic Volume; Vehicle Speed

Introduction

Urban activity in developing cities continues to increase traffic demand, particularly at signalized intersections that function as key conflict points in the road network (Hidiyati et al., 2023). As traffic volume rises, vehicle speed tends to decline, which in turn increases delay and reduces overall network performance (Adibah et al., 2024; Raden Herdian Bayu, Ash Siddiq; Hamzah, Hidayatulloh; M. Saepul, Alam; Shafira Nur, 2024). Understanding the relationship between traffic volume and speed is therefore essential for effective traffic planning and management, especially in urban areas with heterogeneous traffic composition (Aljoufie, 2021; Apriyani et al., 2020; Yakob Alfandy et al., 2024). Recent traffic studies have also demonstrated that the influence of traffic-related variables may vary spatially, indicating the need for geographically weighted approaches when analyzing traffic volume and operational performance (Lin et al., 2024). A global regression model, which is typically used in conventional traffic study techniques, is predicated on the idea that the volume-speed relationship is constant across sites (Cui & Zhang, 2025; Ramadhani et al., 2020). However, in reality, each intersection has different geometric, operational, and environmental characteristics, so the response of vehicle speed to increased traffic volume can vary spatially. In addition, differences in operational characteristics between types of vehicles such as motorcycles, passenger cars, trucks, and buses that cause the level of sensitivity to traffic density is also not the same. Homogeneity assumptions in global models have the potential to simplify the complexity of field conditions and result in less representative estimates (He et al., 2023; Lin et al., 2022). Recent spatial regression studies in developing urban contexts have shown that local spatial models are more capable of capturing non-stationary relationships between transportation variables than conventional global models (Mahmud & Khan, 2022).

The Geographically Weighted Regression (GWR) approach offers an analytical framework capable of capturing the spatial variation of relationships between variables by estimating regression parameters locally (Primasari et al., 2023). This technique makes it possible to identify variations in the impact of traffic volume on vehicle speed at every intersection and movement direction. GWR has been used extensively in studies of urban transportation, however it is still not generally used for multimodal analysis of signalized crossings in emerging cities, especially in the Indonesian context (Mahmud & Khan, 2022; S. Wang et al., 2024; Z. Wang et al., 2023; Zafri & Khan, 2023). Kediri City as a developing city with mixed traffic dominance and diverse vehicle composition faces increasingly complex intersection performance challenges. The high level of activity in the city center and strategic intersections demands an analytical approach that not only considers traffic volume in aggregate, but also takes into account the differences in sensitivity between vehicle types and the spatial characteristics of each intersection (Lin et al., 2022; Nugroho & Dwiatmaja, 2020; Qu et al., 2021; Yakob Alfandy et al., 2024). Thus, this study employs the GWR approach to investigate the relationship between traffic volume and vehicle speed at signalized crossings in Kediri City by considering various vehicle types. This approach is expected to provide an empirical basis for the development of traffic management strategies that are more location-specific, vehicle-type-adaptive, and relevant to traffic management in developing cities, in addition to providing a more comprehensive understanding of the spatial and multimodal heterogeneity of traffic performance at signalized intersections.

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Research Methods

This study examined the connection between vehicle speed and traffic volume at signalized crossings using a quantitative observational design (Abdel-aty et al., 2023; Carrillo-González & Perez-Martinez, 2022; Chen, Bokui; Chen, Yaohui; Wu, 2023; Guerrieri & Parla, 2021; Huang et al., 2018).. Field data were collected from selected intersections in Kediri City during peak-hour traffic conditions. The analysis was conducted separately for motorcycles, passenger cars, trucks, and buses to capture differences in vehicle operating characteristics. The broad link between traffic volume and speed was initially described using OLS regression, and then GWR was used to see if the relationship varied spatially among intersection approaches (Oshan et al., 2019; Primasari et al., 2023; Reda et al., 2023; Shabrina et al., 2021).

Study Area and Observation Units

The study covered eight signalized intersections in Kediri City, namely Semampir, Mojoroto Three-Way, Kawi, Sukorame, Terminal Three-Way, Kemuning, Bandar Ngalim, and Alun-Alun intersection. These locations were selected because they represent important traffic nodes with different operational characteristics, including central business activities, terminal access, mixed traffic movement, and varying traffic volume levels (Klar & Rubensson, 2024). The unit of analysis was not the intersection as a whole, but the directional approach of each intersection. Each approach direction was treated as one spatial observation unit because traffic volume, vehicle composition, and speed may differ between northbound, southbound, eastbound, and westbound movements (Li et al., n.d.). Based on the available approach directions at the eight signalized intersections, 30 observation units were obtained. The model can now account for local differences in traffic performance both within and between intersections thanks to this method. The use of 30 observation units is considered adequate for an exploratory GWR application with a limited number of explanatory variables. Although the dataset offers enough spatial variation to compare local and global regression behavior, it is still insufficient for more intricate multiscale spatial models like Multiscale Geographically Weighted Regression (MGWR), which typically needs a denser spatial sample to accurately estimate variable-specific bandwidths. Therefore, this study focuses on GWR as the most appropriate spatial regression model for the available dataset.

Vehicle Speed Measurement

Vehicle speed measurement is done manually using a stopwatch. At each intersection approach, one observation segment of a certain length is determined. The travel time of the vehicle is measured from the time it enters the segment's starting point to the end point. Measurements are taken for each type of vehicle, namely motorcycles, passenger cars, buses, and trucks. The link between the length of the observation segment and the vehicle's journey duration is used to compute vehicle speed as follows:

$$V_i = \frac{L_i}{t_i}$$

Where:

V_i = The observed vehicle speed at location *i*

L_i = The observation segment length

t_i = The duration of the observed vehicle's journey through the segment

The measured speed values were then averaged by vehicle type and approach direction. This procedure was used to obtain comparable speed values across all observation units. The speed data were separated by vehicle category because each vehicle type has different operational characteristics. Motorcycles generally have higher maneuverability in mixed traffic conditions, while buses and trucks have lower acceleration capability and require larger maneuvering space. Therefore, separate GWR models were estimated for motorcycles, passenger cars, buses, and trucks to identify differences in volume–speed sensitivity between modes.

Spatial Data and Coordinate System

The geographic position of each observation unit was recorded based on the location of the corresponding intersection approach. The coordinates were initially identified using geographic coordinates and then transformed into a projected coordinate system for spatial distance calculation(Konadu et al., 2024). In this study, the spatial data used in this study were projected onto UTM Zone 49S, which is suitable for Kediri City's geographic location, using the WGS 84 coordinate system. The transformation into a projected coordinate system was necessary because the GWR model uses distance-based spatial weighting. Euclidean distance between observation units cannot be calculated accurately using raw latitude and longitude values. Therefore, projected coordinates were used to ensure that spatial distance in the GWR model was expressed in metric units.

Global Regression Model

In order to assess the overall link between traffic volume and vehicle speed without taking geographical variation into account, a global OLS regression model was generated prior to applying GWR. The OLS model makes the assumption that all observation locations have the same impact of traffic volume on vehicle speed. The following is the expression for the global regression model:

$$Y_i = \beta_0 + \sum \beta_1 X_i + \varepsilon_i$$

Where:

Y_i = Average vehicle speed at the observation location *i*

β_0 = Global Intercept

X_i = Traffic Volume at Observation Location *i*

β_1 = Global Regression Coefficient

ε_i = Model error term

The OLS model was used as the baseline for comparison with GWR. The comparison was conducted to determine whether the local spatial model provides better explanatory performance than the global model (Huang et al., 2018; Lessani & Li, 2024; Tang et al., 2020; Yang et al., 2023). Similar model evaluation frameworks have been applied in recent transport studies by comparing global and spatially explicit models to assess whether location-aware approaches improve explanatory performance and spatial interpretation (Mühlematter et al., 2024).

Geographically Weighted Regression Model

At each observation site, spatial variations in the relationship between traffic volume and vehicle speed were captured using Geographically Weighted Regression (GWR). Unlike OLS, GWR allows regression coefficients to vary across space (Mulat et al., 2024; Tesfamichael et al., 2022). Therefore, each observation location has its own local intercept and local coefficient.

$$Y_i = \beta_0(u_i, v_i) + \sum \beta_1(u_i, v_i) X_i + \varepsilon_i$$

Where:

Y_i = Average vehicle speed at the observation location *i*

$\beta_0(u_i, v_i)$ = A local intercept

$\beta_1(u_i, v_i)$ = The local regression coefficient of traffic volume

X_i = The Traffic Volume

(u_i, v_i) = Represents the spatial coordinates of location *i*

ε_i = Model error at the *i* location

The local coefficient $\beta_1(u_i, v_i)$ indicates the degree of sensitivity of vehicle speed to traffic volume at a specific intersection approach. An increase in traffic volume is connected with a decrease in vehicle speed, as indicated by a negative coefficient. A larger negative coefficient indicates a stronger volume-speed sensitivity.

Spatial Weighting and Bandwidth Treatment

The GWR model applies distance-based spatial weighting by assigning greater influence to nearby observations than to distant ones. Because the observation units were irregularly distributed across signalized intersections, an adaptive spatial weighting approach was used to accommodate the uneven spatial distribution of the data. The spatial weight between observation *i* and observation *j* was determined based on the distance between the two observation units. The specific bandwidth value was not explicitly reported in the GWR output; therefore, bandwidth was not interpreted as a separate analytical result. The analysis focused on local coefficients, Local R^2 values, residual comparison, and ANOVA-based comparison between the global OLS and local GWR models. The general form of the spatial weighting function is expressed as follows:

$$w_{ij} = f\left(d_{ij}, b\right)$$

Where:
w_{ij} = Spatial weighting factor assigned to observation *j* during the estimation the local parameter for observation *i*
d_{ij} = Spatial distance separating observation *i* and observation *j*
b = Bandwidth parameter

The GWR model applies distance-based spatial weighting by giving greater influence to nearby observations than to distant ones. Because the observation units were irregularly distributed across signalized intersections, an adaptive spatial weighting approach was used to accommodate uneven spatial distribution. The specific bandwidth value was not explicitly reported in the GWR output; therefore, bandwidth was not interpreted as a separate analytical result. To evaluate the differences between the global OLS and local GWR models, the evaluation took into account residual performance, local parameter estimations, local R2 values, and ANOVA-based comparison (Alisan, 2024).

Model Evaluation

OLS and GWR data were compared to assess the model's performance (Almasi, 2025). The evaluation focused on model-fit indicators, local coefficients, Local R^2 values, and ANOVA-based comparison between the global and local models. Local R^2 was used to identify the extent to which traffic volume explains vehicle speed variation at each observation location. The ANOVA GWR procedure was used to assess whether the GWR model improves the explanatory performance compared with the global OLS model. The analysis includes three main components: global residuals, GWR improvement, and GWR residuals(Jawarneh & Abulibdeh, 2024). A lower residual value in the GWR model indicates that the local spatial model better captures the spatial heterogeneity of the volume–speed relationship. The model interpretation was conducted separately for motorcycles, passenger cars, buses, and trucks. This separation was necessary because each vehicle type has different operational behavior under congested intersection conditions. The results were then interpreted to identify which intersections and vehicle types show the strongest spatial sensitivity to changes in traffic volume.

Research Results and Discussion

Research Data

The traffic data were obtained from field surveys conducted at eight major signalized intersections in Kediri City. The observation unit was defined as the directional approach of each intersection rather than the intersection as a whole. Based on the available approach directions, a total of 30 observation units were used in the analysis. The key variables analyzed in this study were peak-hour traffic volume and mean vehicle speed for four categories: motorcycles, passenger cars, buses, and trucks. To avoid presenting an overly long raw-data table in the main manuscript, the detailed observation data for the 30 intersection approaches are not shown in the main text. Instead, the data are summarized using descriptive statistics. The full observation dataset may be provided as an appendix or supplementary material. This presentation format was adopted to enhance readability without omitting the essential descriptive information on traffic volume and vehicle speed within the study area.

Table 1. Descriptive Statistics of Traffic Volume and Vehicle Speed

Variable	Mean	Standard Deviation	Minimum	Maximum
Traffic volume (pcu/hour)	453.51	252.05	114.80	1,158.00
Motorcycle speed (km/h)	10.45	2.27	4.19	13.75
Passenger car speed (km/h)	9.50	2.34	3.78	13.20
Bus speed (km/h)	9.56	1.92	7.21	13.10
Truck speed (km/h)	8.85	1.75	4.97	12.10

(Source: Authors' analysis, 2026)

Table 1 shows that traffic volume at the observed signalized intersections varies considerably. The average traffic volume was 453.51 pcu/hour, with a standard deviation of 252.05 pcu/hour. The minimum observed volume was 114.80 pcu/hour, while the maximum reached 1,158.00 pcu/hour. This wide range indicates substantial differences in traffic intensity among intersection approaches. Therefore, using a single global model may oversimplify the actual variation in field conditions. In terms of speed, motorcycles had the highest average speed, at 10.45 km/h. This condition can be associated with the higher maneuverability of motorcycles in mixed traffic conditions. Passenger cars had an average speed of 9.50 km/h, while buses and trucks recorded average speeds of 9.56 km/h and 8.85 km/h, respectively. Trucks had the lowest average speed, which can be explained by their lower acceleration capability, larger vehicle dimensions, and greater space requirements when moving through signalized intersection approaches.

Spatially, Kemuning Intersection and Alun-Alun Intersection showed relatively high traffic volumes compared with the other intersections, whereas Kawi Intersection had lower traffic volume but relatively higher vehicle speeds. This pattern suggests that the relationship between traffic volume and vehicle speed is not uniform across locations. Therefore, a local spatial regression approach such as GWR is required to capture variations in volume–speed sensitivity among intersection approaches.

Global Regression Results (OLS)

Before estimating the GWR model, OLS regression was used to establish a global baseline. The OLS framework assumes that the relationship between traffic volume and vehicle speed remains the same across observation units, so spatial heterogeneity among intersection approaches is not explicitly represented (Almasi et al., 2023; Rhee et al., 2016; Zafri & Khan, 2023). The OLS results indicate that traffic volume, segment length, and delay did not strongly explain variations in vehicle speed at the global scale. The t-values for traffic volume, segment length, and delay were 0.389, -0.105, and -0.054, respectively (Pradigta et al., 2025). These values are far below commonly used statistical significance thresholds. Therefore, the global model did not provide strong evidence of a uniform relationship between the explanatory variables and vehicle speed across all observed locations.

Table 2. Global Regression Coefficient (OLS) Results

Variable	Estimate	Standard Error	t-value	Interpretation
Traffic Volume	88.49	227.41	0.389	Weak Global Effect
Segment Length	–22.37	214.08	–0.105	Weak Global Effect
Delay	–12.38	230.58	–0.054	Weak Global Effect

(Source: Spatial Regression Model Analysis Article 2025 (Pradigta et al., 2025))

The OLS results demonstrate that changes in vehicle speed across the observed intersection approaches could not be sufficiently explained by the global regression model. The low t-values indicate that the relationship between traffic volume, segment length, delay, and vehicle speed cannot be sufficiently represented when all intersection approaches are treated as a homogeneous system. This finding should not be interpreted as evidence that traffic volume has no influence on vehicle speed. The impact of traffic volume on vehicle speed is not geographically uniform, which is a better explanation. At some intersection approaches, an increase in traffic volume may have a strong impact on speed reduction, whereas at other approaches the effect may be weaker due to differences in geometry, signal operation, side friction, vehicle composition, turning movements, and local traffic conditions. Thus, the weak performance of the OLS model provides a methodological basis for applying GWR. The GWR model is more appropriate because it estimates local regression coefficients and allows the volume–speed relationship to vary across space.

GWR Model Results

The account for local variation in the correlation between vehicle speed and traffic volume across intersection approaches, the GWR model was utilized. Unlike OLS, this approach permits regression parameters to vary spatially. Therefore, this model can identify which intersection approaches are more sensitive to changes in traffic volume. The GWR results show that all local coefficients of traffic volume were negative for all vehicle types. This suggests that a drop in vehicle speed is typically linked to an increase in traffic volume. However, the magnitude of this effect differs by vehicle type and location. Table 3 presents the local GWR coefficients and Local R² values for each intersection approach and vehicle type. This table is retained in the main manuscript because it represents the core empirical output of the GWR analysis. The local coefficients provide direct evidence of spatial heterogeneity in the volume–speed relationship, while Local R² indicates the local explanatory power of the model at each observation unit.

Table 3. Local Coefficients (β) and Local R² of the GWR Model for All Vehicle Types

Intersection	Directions	Motorcycle		Car		Truck		Bus	
Semampir Intersection	South	−1.418	0.644	−1.962	0.748	−2.182	0.781	−2.041	0.756
Semampir Intersection	East	−1.182	0.589	−1.603	0.695	−1.936	0.742	−1.812	0.721
Semampir Intersection	West	−1.356	0.603	−1.845	0.712	−2.061	0.769	−1.926	0.743

Intersection	Directions	Motorcycle		Car		Truck		Bus	
Mojoroto Three-Way Intersection	East	−1.214	0.552	−1.684	0.662	−1.924	0.706	−1.768	0.689
Mojoroto Three-Way Intersection	North	−1.389	0.601	−1.912	0.701	−2.138	0.741	−1.932	0.712
Mojoroto Three-Way Intersection	South	−1.072	0.578	−1.548	0.673	−1.802	0.713	−1.654	0.681
Kawi Intersection	North	−0.912	0.421	−1.214	0.523	−1.412	0.566	−1.276	0.542
Kawi Intersection	South	−0.768	0.398	−1.086	0.501	−1.286	0.548	−1.148	0.521
Kawi Intersection	East	−0.845	0.407	−1.142	0.512	−1.338	0.552	−1.193	0.528
Kawi Intersection	West	−0.801	0.423	−1.118	0.536	−1.321	0.571	−1.221	0.549
Sukorame Intersection	North	−0.536	0.318	−0.842	0.412	−0.986	0.431	−0.914	0.418
Sukorame Intersection	South	−0.382	0.289	−0.768	0.389	−0.914	0.418	−0.842	0.402
Sukorame Intersection	East	−0.410	0.301	−0.801	0.401	−0.942	0.424	−0.871	0.409
Sukorame Intersection	West	−0.465	0.296	−0.823	0.396	−0.965	0.419	−0.896	0.415
Terminal Three-Way Intersection	North	−1.244	0.569	−1.756	0.689	−2.012	0.733	−1.842	0.708
Terminal Three-Way Intersection	West	−1.118	0.552	−1.624	0.661	−1.876	0.706	−1.706	0.684
Terminal Three-Way Intersection	East	−1.008	0.541	−1.582	0.648	−1.834	0.694	−1.664	0.671
Kemuning Intersection	North	−1.196	0.582	−1.703	0.704	−1.956	0.748	−1.798	0.724
Kemuning Intersection	South	−1.476	0.651	−2.034	0.782	−2.312	0.821	−2.108	0.792
Kemuning Intersection	East	−1.321	0.638	−1.912	0.761	−2.186	0.803	−1.986	0.774
Kemuning Intersection	West	−1.201	0.621	−1.845	0.743	−2.104	0.789	−1.921	0.758
Bandar Ngalim Intersection	North	−1.412	0.667	−1.968	0.791	−2.241	0.832	−2.034	0.801
Bandar Ngalim Intersection	South	−1.168	0.531	−1.642	0.631	−1.842	0.662	−1.704	0.641

Intersection	Directions	Motorcycle		Car		Truck		Bus	
Bandar Ngalim Intersection	East	−1.034	0.512	−1.518	0.612	−1.724	0.641	−1.586	0.622
Bandar Ngalim Intersection	West	−0.934	0.498	−1.463	0.598	−1.681	0.628	−1.543	0.608
Alun-Alun Intersection	North	−1.102	0.535	−1.587	0.639	−1.795	0.669	−1.667	0.649
Alun-Alun Intersection	South	−1.692	0.724	−2.216	0.824	−2.486	0.861	−2.243	0.832
Alun-Alun Intersection	East	−1.548	0.701	−2.084	0.801	−2.354	0.842	−2.112	0.814
Alun-Alun Intersection	West	−1.415	0.712	−1.973	0.812	−2.218	0.853	−1.996	0.821

Note: β denotes the local coefficient of traffic volume. A more negative β indicates stronger sensitivity of vehicle speed to increasing traffic volume. Local R^2 indicates the local explanatory power of the GWR model at each intersection approach.

(Source: Authors' analysis, 2026)

Table 3 shows that the local coefficients are negative for all vehicle types, indicating that higher traffic volume is associated with lower vehicle speed at signalized intersection approaches. However, the magnitude of this effect varies by mode and location. Motorcycles show the lowest sensitivity, reflecting their higher maneuverability in mixed traffic, whereas passenger cars are more affected by queue formation, signal delay, and vehicle interactions. Heavy vehicles exhibit the strongest sensitivity, particularly trucks, due to their lower acceleration capability, larger dimensions, and greater maneuvering-space requirements. Buses also show high volume–speed sensitivity, especially at approaches with intensive vehicle interaction and queue development. Spatially, the south approach of Alun-Alun Intersection shows the strongest sensitivity across all vehicle types, as indicated by the most negative local coefficients and the highest Local R^2 values. This pattern reflects the role of Alun-Alun as a major urban activity center with high travel demand, mixed traffic composition, turning movements, and peak-hour queue formation. Kemuning and Semampir intersections also show relatively strong volume–speed sensitivity, while Sukorame and Kawi show weaker effects. Lower Local R^2 values at these locations suggest that speed variation may also be influenced by other operational factors, such as approach geometry, effective road width, side friction, signal phasing, and surrounding land use. Overall, the GWR results demonstrate that the volume–speed relationship at signalized intersections in Kediri City is spatially heterogeneous. Therefore, traffic management should be location-specific and vehicle-sensitive, particularly at approaches with highly negative local coefficients and high Local R^2 values. Recommended interventions include signal timing evaluation, queue management, heavy-vehicle control, and reduction of turning or lateral conflicts at critical approaches.

ANOVA-Based Comparison Between OLS and GWR

The relative performance of the local GWR model and the global OLS model was assessed using the ANOVA-based GWR comparison. Results indicate that the GWR model produced improvement components for all vehicle types, although the magnitude of improvement varied across modes. Trucks had the highest F-value, followed by buses, while motorcycles and passenger cars had lower F-values. The ANOVA table is already described in Table 4.

Table 4. ANOVA Results of the GWR Models for All Vehicle Types

Vehicle Type	Components	SS	DF	MS	F
Motorcycle (MC)	Global Residuals	4.037.662,63	26	–	–
	GWR Improvement	210.079,88	2	98.820,61	**0.616**
	GWR Residuals	3.827.582,75	23	160.323,45	–
Car	Global Residuals	4.116.592,44	26	–	–
	GWR Improvement	228.593,46	2	107.055,74	**0.657**
	GWR Residuals	3.887.998,98	23	162.918,24	–
Truck	Global Residuals	2.801.155,77	26	–	–
	GWR Improvement	231.568,98	4	56.312,82	**2.483**
	GWR Residuals	496.442,57	21	22.681,24	–
Bus	Global Residuals	1.032.370,79	26	–	–
	GWR Improvement	119.589,65	1	61.412,38	**1.618**
	GWR Residuals	912.781,14	24	37.949,25	–

(Source: Authors' analysis, 2026)

The ANOVA-based comparison indicates that the local GWR model provides different levels of explanatory improvement across vehicle categories. The reduction in residual values suggests that spatially varying coefficients can capture part of the volume–speed relationship that is not represented by the global OLS model. However, the improvement is not identical for all modes. The most apparent improvement occurs for trucks, followed by buses, whereas motorcycles and passenger cars show relatively smaller gains. This result implies that the spatial effect of traffic volume is more pronounced for heavy vehicles, which are more constrained by acceleration capability, vehicle size, and maneuvering space at signalized intersection approaches.

Spatial Visualization of Traffic Volume and GWR Outputs

Figure 1. Location Map of the Observed Signalized Intersections

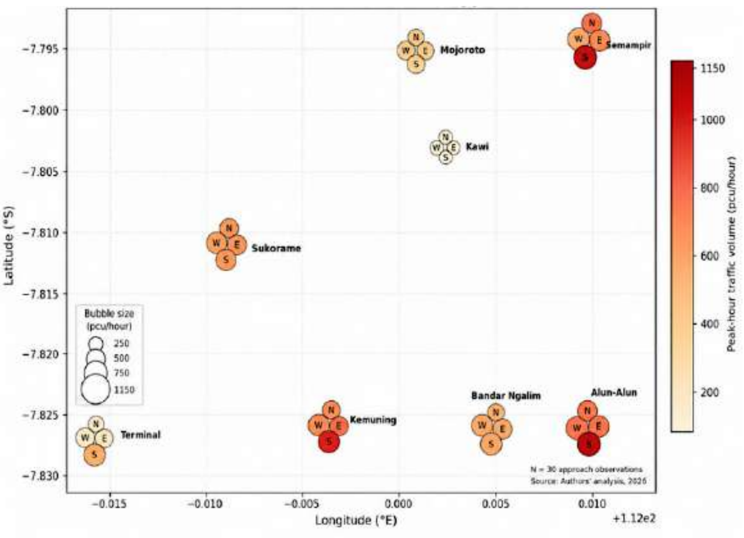
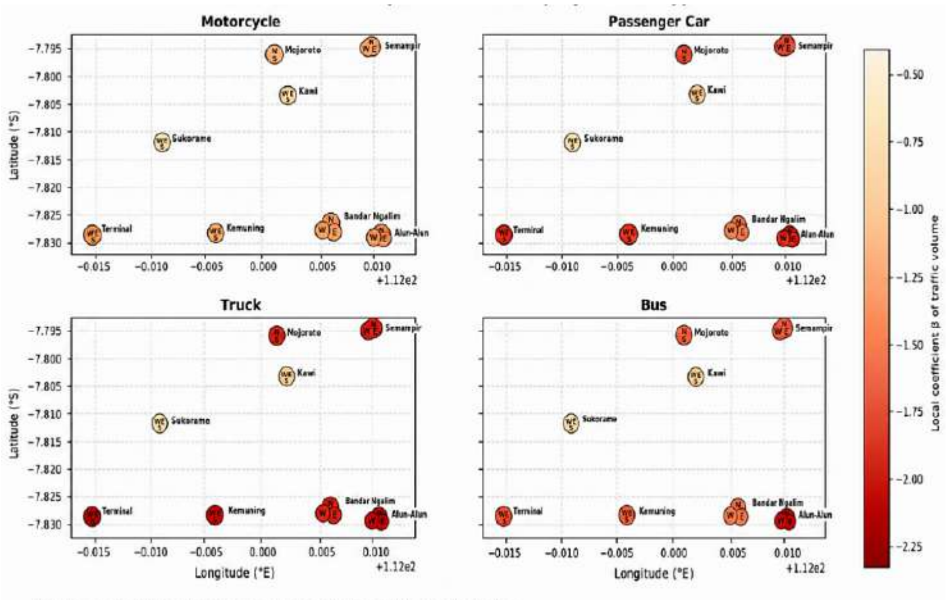


Figure 2. Spatial Distribution of Peak-Hour Traffic Volume

The spatial presentation in Figure 1 provides the geographical context of the eight signalized intersections included in the analysis. The actual unit of analysis in this study is the directional approach of each intersection, even if the map shows intersection points. This distinction is important because traffic flow, vehicle composition, and speed conditions may differ between approaches within the same intersection. Therefore, the spatial configuration of the observed locations must be understood before interpreting the GWR outputs. Figure 2 illustrates the spatial pattern of peak-hour traffic volume in the study area. The map shows that traffic demand is distributed unevenly across the observed intersections. Some locations carry relatively high traffic loads, while others experience lower traffic intensity. This irregular pattern offers a preliminary clue that the impact of traffic congestion on vehicle speed might not be consistent over space. At approaches with higher traffic demand, queue development, vehicle interaction, turning conflicts, and speed reduction are more likely to occur.



Note: More negative β values indicate stronger sensitivity of vehicle speed to increasing traffic volume.

Figure 3. Spatial Distribution of Local GWR Coefficients

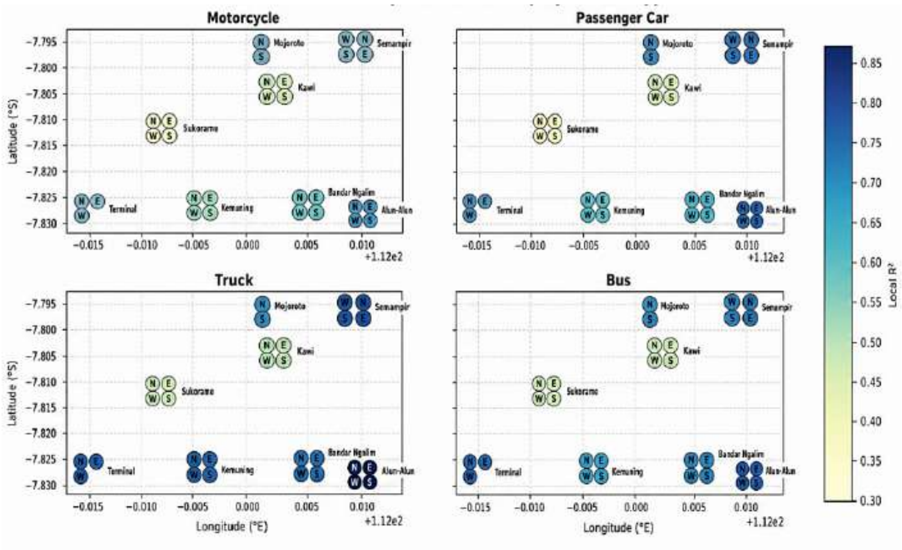


Figure 4. Spatial Distribution of Local R² Values from the GWR Model

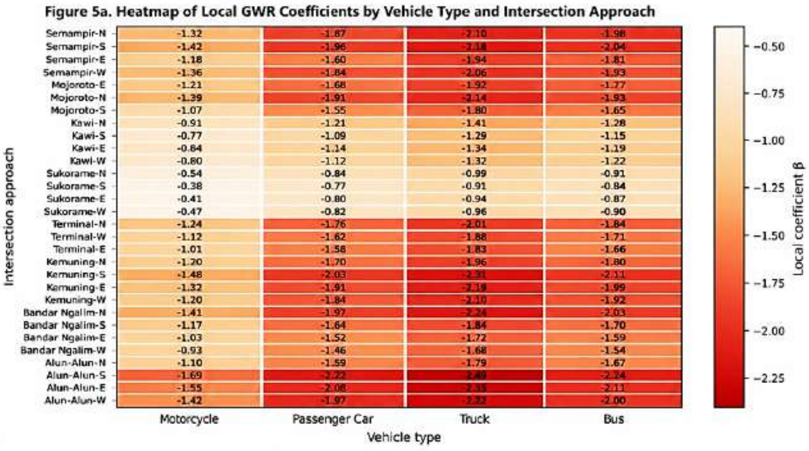


Figure 5a. Heatmap of Local GWR Coefficients by Vehicle Type and Intersection Approach

Intersection approach	Motorcycle	Passenger Car	Truck	Bus
Semampir-N	-1.32	-1.87	-2.10	-1.98
Semampir-S	-1.42	-1.96	-2.18	-2.04
Semampir-E	-1.18	-1.60	-1.94	-1.81
Semampir-W	-1.36	-1.84	-2.06	-1.93
Mojoroto-E	-1.21	-1.68	-1.92	-1.77
Mojoroto-N	-1.39	-1.91	-2.14	-1.93
Mojoroto-S	-1.07	-1.55	-1.80	-1.65
Kawi-N	-0.91	-1.21	-1.41	-1.28
Kawi-S	-0.77	-1.09	-1.29	-1.15
Kawi-E	-0.84	-1.14	-1.34	-1.19
Kawi-W	-0.80	-1.12	-1.32	-1.22
Sukorame-N	-0.54	-0.84	-0.99	-0.91
Sukorame-S	-0.38	-0.77	-0.91	-0.84
Sukorame-E	-0.41	-0.80	-0.94	-0.87
Sukorame-W	-0.47	-0.82	-0.96	-0.90
Terminal-N	-1.24	-1.76	-2.01	-1.84
Terminal-W	-1.12	-1.62	-1.88	-1.71
Terminal-E	-1.01	-1.58	-1.83	-1.66
Kemuning-N	-1.20	-1.70	-1.96	-1.80
Kemuning-S	-1.48	-2.03	-2.31	-2.11
Kemuning-E	-1.32	-1.91	-2.19	-1.99
Kemuning-W	-1.20	-1.84	-2.10	-1.92
Bandar Ngalim-N	-1.41	-1.97	-2.24	-2.03
Bandar Ngalim-S	-1.17	-1.64	-1.84	-1.70
Bandar Ngalim-E	-1.03	-1.52	-1.72	-1.59
Bandar Ngalim-W	-0.93	-1.46	-1.68	-1.54
Alun-Alun-N	-1.10	-1.59	-1.79	-1.67
Alun-Alun-S	-1.69	-2.22	-2.49	-2.24
Alun-Alun-E	-1.55	-2.08	-2.35	-2.11
Alun-Alun-W	-1.42	-1.97	-2.22	-2.00

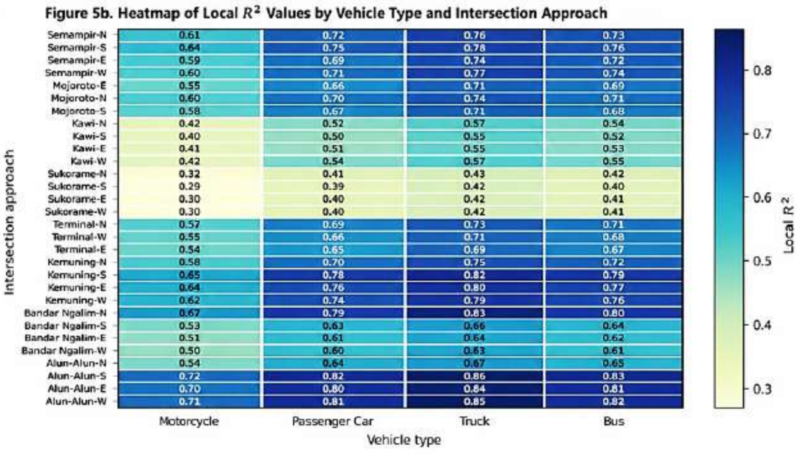


Figure 5b. Heatmap of Local R^2 Values by Vehicle Type and Intersection Approach

Intersection approach	Motorcycle	Passenger Car	Truck	Bus
Semampir-N	0.61	0.72	0.76	0.73
Semampir-S	0.64	0.75	0.78	0.76
Semampir-E	0.59	0.69	0.74	0.72
Semampir-W	0.60	0.71	0.77	0.74
Mojoroto-E	0.55	0.66	0.71	0.69
Mojoroto-N	0.60	0.70	0.74	0.71
Mojoroto-S	0.58	0.67	0.71	0.68
Kawi-N	0.42	0.52	0.57	0.54
Kawi-S	0.40	0.50	0.55	0.52
Kawi-E	0.41	0.51	0.55	0.53
Kawi-W	0.42	0.54	0.57	0.55
Sukorame-N	0.32	0.41	0.43	0.42
Sukorame-S	0.29	0.39	0.42	0.40
Sukorame-E	0.30	0.40	0.42	0.41
Sukorame-W	0.30	0.40	0.42	0.41
Terminal-N	0.57	0.69	0.73	0.71
Terminal-W	0.55	0.66	0.71	0.68
Terminal-E	0.54	0.65	0.69	0.67
Kemuning-N	0.58	0.70	0.75	0.72
Kemuning-S	0.65	0.78	0.82	0.79
Kemuning-E	0.64	0.76	0.80	0.77
Kemuning-W	0.62	0.74	0.79	0.76
Bandar Ngalim-N	0.67	0.79	0.83	0.80
Bandar Ngalim-S	0.53	0.63	0.66	0.64
Bandar Ngalim-E	0.51	0.61	0.64	0.62
Bandar Ngalim-W	0.50	0.60	0.63	0.61
Alun-Alun-N	0.54	0.64	0.67	0.65
Alun-Alun-S	0.72	0.82	0.86	0.83
Alun-Alun-E	0.70	0.80	0.84	0.81
Alun-Alun-W	0.71	0.81	0.85	0.82

Figure 5. Heatmaps of Local GWR Coefficients and Local R² Values

The spatial visualization of the GWR outputs is presented to strengthen the interpretation of the numerical results in Table 3. Figure 3 displays the local coefficients of traffic volume for each vehicle type. More negative coefficient values indicate that vehicle speed is more sensitive to increases in traffic volume at the corresponding approach. Figure 4 presents the Local R^2 values, which show the extent to which traffic volume explains speed variation locally. Meanwhile, Figure 5 summarizes the local coefficients and Local R^2 values in heatmap form, allowing comparison across vehicle types and intersection approaches. These visualizations confirm that the relationship between traffic volume and vehicle speed is spatially heterogeneous. The effect is not only different between locations, but also varies by vehicle type. Trucks and buses generally show stronger sensitivity to increasing traffic volume than motorcycles and passenger cars. This condition is consistent with the operational characteristics of heavy vehicles, which require larger maneuvering space and have lower acceleration performance. Therefore, rather than treating all locations equally, traffic management methods at signalized crossings should be developed depending on local traffic conditions and vehicle-type characteristics.

Discussion of Model Limitations and Spatial Implications

When interpreting the study's findings, a number of limitations must be taken into account. Initially, thirty observation units obtained from directional approaches at eight signalized junctions were used for the research. This dataset is sufficient for an exploratory application of GWR with a limited number of explanatory variables. However, it is still relatively limited for more advanced spatial models such as MGWR, which require a larger and denser spatial dataset to estimate variable-specific spatial scales more reliably. Second, the interpretation of the GWR model was focused on local coefficients, Local R^2 values, residual comparison, and ANOVA-based model evaluation. Since the bandwidth value was not explicitly reported in the model output, it was not discussed as a separate analytical finding. Third, this study examined vehicle speed primarily as a function of traffic volume. In actual intersection operations, speed may also be affected by signal timing, queue length, approach width, side friction, turning movement proportion, geometric layout, and vehicle composition. Despite these limitations, the findings provide important practical implications. Approaches with more negative local coefficients and higher Local R^2 values indicate locations where traffic volume has a stronger influence on speed reduction. Alun-Alun and Kemuning intersections, for example, require more focused operational treatment, including signal timing review, queue management, heavy-vehicle control, and reduction of lateral or turning conflicts. Conversely, approaches with lower Local R^2 values should be examined further because speed variation at those locations may be controlled by factors other than traffic volume. These results support the need for spatially adaptive traffic management at urban signalized intersections.

Conclusion

This study demonstrates that the volume–speed relationship at signalized intersections in Kediri City is spatially heterogeneous. The OLS model only provides a general estimate, whereas GWR reveals local variations across intersection approaches and vehicle types. Higher traffic volume generally reduces vehicle speed, but the effect differs by mode. Motorcycles show the weakest sensitivity due to greater maneuverability, while trucks and buses experience stronger speed reductions because of their larger dimensions, lower acceleration capability, and greater space requirements. Spatially, Alun-Alun and Kemuning intersections exhibit stronger volume–speed sensitivity, as shown by more negative local coefficients and higher Local R^2 values. The ANOVA comparison further indicates that GWR improves the global model differently across modes, with the most notable improvement for trucks. Overall, this study provides empirical evidence for location-specific and vehicle-sensitive traffic management at urban signalized intersections.

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