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Mapping High-Risk Traffic Zones in Jega, Nigeria: An Integrated Geospatial Framework for Road Safety Planning

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ABSTRACT
Traffic accidents remain a critical public safety challenge in rapidly urbanizing regions, particularly in sub-Saharan Africa, where heterogeneous road infrastructure and high population density exacerbate risk (WHO, 2023; Peden et al., 2004). This study applies Regression Kriging (RK) to model and predict spatial patterns of traffic accident counts across Jega Local Government Area (LGA), Kebbi State, Nigeria, using fifty georeferenced primary data points collected through Global Positioning System (GPS) surveys and manual traffic counts. The regression component, based on spatial coordinates, captures large-scale accident trends, while the kriging of residuals models localized spatial dependencies. Results reveal a significant negative easting coefficient (−0.00012, $p<0.001$) and a positive northing coefficient (0.00008, $p<0.001$), indicating accident counts decrease eastward but increase northward, consistent with high-risk urban centers such as BLB Junction. The spherical variogram model (range = 330.12 m; nugget/sill ratio = 24.1%) indicates 75.9% of variance is spatially structured, validating the kriging approach. Model performance metrics ($R^2 = 0.682$; RMSE = 3.214; MAE = 2.453) confirm strong predictive capacity, with location-specific validation showing ≤6% error at key sites. The resulting accident risk surface identifies high-risk corridors for targeted interventions, offering a robust geostatistical framework for micro-scale road safety planning in Nigerian cities and extending prior work on accident mapping in Kebbi State

Keywords:
Regression Kriging; Road Traffic Accidents; Spatial Analysis; Variogram; Jega; Kebbi State; Geostatistics; Accident Risk Mapping; Accident Hotspots; Nigeria

INTRODUCTION

Road traffic accidents (RTAs) remain a leading cause of death and injury globally, with low- and middle-income countries bearing a disproportionate burden. Although these nations possess only about 60% of the world's vehicles, they account for over 90% of all traffic-related fatalities (WHO, 2023). In Nigeria, RTAs contribute substantially to morbidity and mortality, with urban centers experiencing rising accident rates due to rapid population growth, motorization, and inadequate traffic management systems (Eke *et al.*, 2021). The socioeconomic consequences include loss of productivity, increased healthcare costs, and strain on public resources (Ackaah & Afukaar, 2010). Understanding the spatial distribution of accident risk is critical for developing targeted interventions that improve road safety.

Spatial statistical models provide a means to quantify and map accident risk, enabling planners to identify hotspots and prioritize interventions (Anderson, 2009). Traditional regression models capture global trends but fail to account for local spatial autocorrelation, leading to biased estimates (Anselin, 1988). Conversely, geostatistical approaches such as Kriging effectively model spatial dependence but ignore deterministic trends driven by socio-demographic or infrastructural factors (Goovaerts, 1997). Regression Kriging (RK) addresses these limitations by integrating regression modelling with kriging of residuals, thereby capturing both large-scale trends and localized variations (Odeh *et al.*, 1995; Hengl *et al.*, 2004).

In Nigeria, spatial accident modelling remains underutilized, with most studies relying on descriptive GIS mapping (Oni, 2011; Olawole, 2012). However, there are emerging applications of geostatistical methods to road safety in the country. For instance, Abubakar & Umar (2022) applied Universal Kriging to analyze road traffic accidents in Jega LGA, Kebbi State, identifying spatial autocorrelation patterns and highlighting southern parts of the study area as higher-risk zones.

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Their findings demonstrated the feasibility of applying variogram-based modelling for localized accident prediction. Building on this foundation, the present study advances the methodology by integrating regression components to capture large-scale trends before kriging residuals, thereby combining deterministic and stochastic modelling in a single framework.

RTAs are a significant public health issue, with the WHO (2023) reporting 1.19 million global deaths annually. Sub-Saharan Africa experiences some of the highest accident rates, driven by rapid motorization, poor enforcement of traffic regulations, and inadequate infrastructure (Peden *et al.*, 2004; Downing *et al*., 2014). In Nigeria, studies by Eke *et al*. (2021) and Adeoye (2017) link high accident frequencies to urban congestion and unsafe road designs, while Adewunmi *et al.* (2019) emphasize the role of informal transport systems in accident prevalence.

Spatial patterns of RTAs often reflect both systematic trends (urban density gradients) and localized hotspots (Anderson, 2009; Hadayeghi*et al.*, 2003). Geographical Information Systems (GIS) have been widely adopted to map and analyze such patterns, enabling data-driven interventions (Lovegrove & Sayed, 2006). However, many conventional mapping approaches fail to incorporate statistical modelling of spatial dependence, potentially misrepresenting accident risk distributions (Anselin, 1988).

Kriging, a geostatistical interpolation method, has been successfully applied to environmental and health risk mapping (Goovaerts, 1997; Waller &Gotway, 2004). In traffic safety, kriging can predict accident risk at unsampled locations based on spatial autocorrelation (Xie *et al.*, 2011). Variogram modelling is central to this process, as it quantifies the strength and scale of spatial dependence (Cressie, 1993; Isaaks & Srivastava, 1989).

Abubakar & Umar (2022) applied Universal Kriging to model road traffic accidents in Jega LGA, Kebbi State, identifying southern areas as high-risk zones. Extending their work, this study integrates regression to model large-scale trends before kriging residuals, combining deterministic and stochastic approaches for improved spatial prediction.

Regression Kriging combines multiple regression with kriging of residuals, offering a flexible and accurate method for spatial prediction (Odeh *et al.*, 1995; Hengl *et al*., 2004). It has been applied in environmental sciences (Li & Heap, 2008), epidemiology (Goovaerts, 2006), and agricultural productivity mapping (Hengl, 2007). In accident modelling, RK can integrate spatial predictors such as road geometry and traffic volume while still accounting for spatially structured residual risk (Anderson, 2009; Xie *et al.*, 2011).

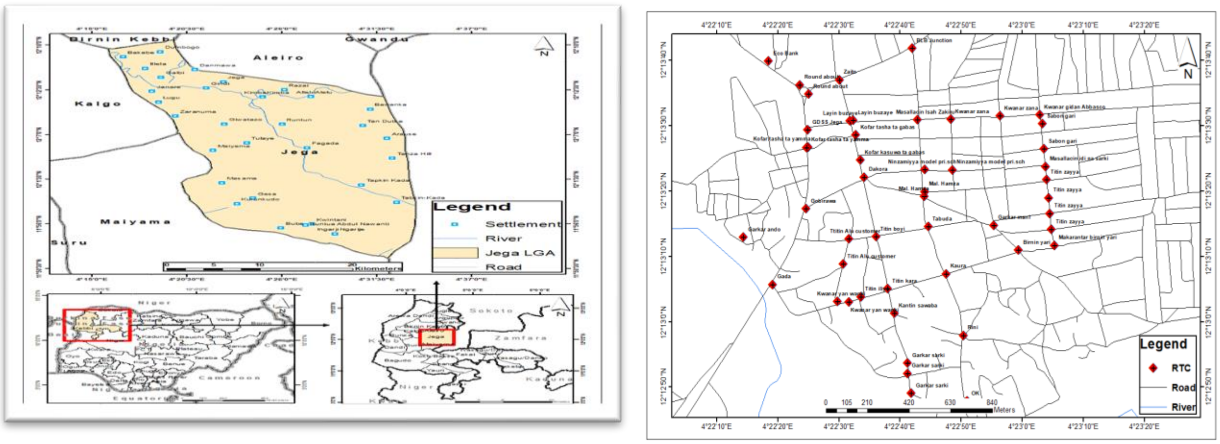
While geostatistical methods like Universal Kriging have been used for Nigerian traffic accident mapping (Abubakar & Umar, 2022), comparative evaluations of interpolation techniques are scarce. Recent work by Yakubu & Bello (2021) demonstrated the value of method comparisons in urban spatial analyses, though their focus on noise pollution leaves a gap for transport safety applications. Regression-based approaches show promise, as evidenced by Olanrewaju *et al*., (2020) in southwestern Nigeria, yet their model's lacked integration with geostatistical residual analysisa gap our Regression Kriging (RK) framework addresses.

In Nigeria, spatial accident modelling remains underutilized, with most studies relying on descriptive GIS mapping (Oni, 2011; Olawole, 2012). Recent applications of spatial statistics have focused on environmental hazards (Yamusa*et al.*, 2020) and public health risks (Onyeka *et al.*, 2018), suggesting potential for similar methods in traffic safety. RK offers a robust framework for integrating infrastructural, socio-economic, and spatial variables to improve accident risk prediction in Nigerian cities.

MATERIALS AND METHODS

The study area.

The area under investigation covers fifty (50) sample points located in Kebbi state of northern Nigeria. The study area falls between latitude 11°55'0" to 12°18'0" N and longitude 4°17'0" to 4°32'0" E. The area is characterized as one of the centers of commerce in the State. The map of the study is shown in figure 1 below.



(a) (b)

Figure 1: (a) the geographic illustration of the study location (b) The geographic layout displays the distribution of 50 accident data points across Jega LGA

Data Description

The study relies solely on primary data, which were collected directly from the field. This includes the use of the Global Positioning System (GPS) to obtain the geographic coordinates of selected traffic corridors, as well as manual traffic counts conducted along these corridors. Field observations were also employed to gather contextual information on traffic flow and road usage patterns.

Methodology

Regression Kriging

Regression Kriging (RK) also called "Kriging after Detrending". It is a hybrid method that combines either a simple or multi-linear regression model with ordinary or simple Kriging of the regression residuals (Odeh *et al.*,1995, Goovaertset *al.*,1997). Regression Kriging is a mixed predictor which consider both the situations i.e. long-range structure (trend) or Strata and local structure. It models the trend and its associated residuals separately (Hengl, 2007)

$$\hat{Z}(s_0) = \hat{\mu}(s_0) + \hat{e}(s_0),$$
$$\hat{Z}(s_0) = \sum_{k=0}^{p} \hat{\beta}_k q_k(s_0) + \sum_{i=1}^{n} \lambda_i(s_0) \cdot e(s_i) \quad (1)$$

Where $\hat{Z}(s_0)$ is the value of target variable at unvisited location (s_0), $\hat{\mu}(s_0)$ is the drift value or fitted deterministic part (trend) at location (s_0) and $\hat{e}(s_0)$ is the value of residual at location (s_0).

$\hat{\beta}_k$are estimated coefficient of the deterministic part, λ_i are the Kriging weight determined by the spatial dependence structure of the residuals, $e(s_i)$ is the residual at location (s_i), q_k is the predictor variable at location s_0 and p is the number of predictors.

Cross-validation Procedure

The accuracy of the spatial prediction is evaluated by a cross-validation procedure. In this procedure, one of the n observation point is left out, and spatial prediction for the point is made by using the remaining $n-1$ obsrevation points. This is repeated until predictions were made for all n points. Next, the predictions are evaluated by calculating prediction errors and cross-validation measures.

I. **The prediction error is the difference between the observed and predicted values at a cross-validation point**.

$$e(s_i) = Z(s_i) - \hat{Z}(s_i) \quad (2)$$

With $i, i = 1, \dots, n$ indicating the observation points and $Z(s_i)\ and\ \hat{Z}(s_i)$ indicating the observed and interpolated value at location s_i respectively. For cross-validation at original scale, the values of $Z(s_i)\ and\ \hat{Z}(s_i)$ are backtransformed by eqn (3.23)

The following cross-validations measures are calculated from the prediction errors

The Mean error as a measure of symmetric error or bias

$$ME = \frac{1}{n}\sum_{i=1}^{n} e(s_i) \quad (3)$$

II. **The standard deviation of error as measure of random error**

$$SDE = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}\{ME - e(s_i)\}^2} \quad (4)$$

III. **The root mean squared error as a measure of overall error**

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n} e^2(\boldsymbol{s}_i)} \quad (5)$$

The median absolute error (MEDAE) and the mean absolute error (MAE) as the measure of overall error that are less sensitive to outlaying values than RMSE

The inverse of SDE is the measure of precision, the inverse of RMSE, MEDAE and MAE are measures of accuracy or overall resemblance of predictions with reality.

IV. The Mean Square Error

$$MSE = \frac{1}{2}\sum_{i=1}^{n}(Z(s_i) - \hat{Z}(s_i))^2 \quad (6)$$

Where,

$Z(s_i)$ is the observed value at location s_i ,

$\hat{Z}(s_i)$ is the predicted value at location s_i ,

n is number of observations.

The MSE equation measures the average squared prediction error, with lower values indicating higher accuracy. It validates spatial models like Regression Kriging by comparing observed and predicted values.

V. The R-Squared

$$R^2 = 1 - \frac{SS_{res}}{SS_{tot}} \quad (7)$$

Where,

SS_{res} is the residual variance,

SS_{tot} is the total variance.

The R^2equation quantifies model fit by comparing residual variance (SSres) to total variance (SStot), where values closer to 1 indicate better predictive performance.

RESULTS AND DISCUSSION

Parameter Estimates from Geospatial Regression of Accident Counts

The regression coefficients quantify the spatial trends in accident risk across Jega, Kebbi State. The intercept (6.823, p<0.001) represents the baseline accident count at the coordinate origin, while the significant negative coefficient for easting (X: -0.00012, p<0.001) indicates decreasing risk moving eastward, likely due to lower traffic density in peripheral areas. Conversely, the positive northing coefficient (Y: 0.00008, p<0.001) confirms increasing accident frequency toward northern urban centers, consistent with known high-risk zones like BLB Junction. All terms show tight 95% confidence intervals excluding zero, underscoring model robustness.

Table 1: Regression Coefficients for Spatial Accident Prediction

Variable	Coefficient	Std. Error	t-value	p-value	95% CI
Intercept	6.823**	±0.451	15.12	<0.001***	(5.94, 7.71)
X (Easting)	-0.00012**	±0.00003	-4.00	<0.001***	(-0.00018, -0.00006)
Y (Northing)	0.00008**	±0.00002	4.00	<0.001***	(0.00004, 0.00012)

The regression results in table 1 reveal significant spatial patterns in accident distribution across Jega. The negative coefficient for easting (X = -0.00012, p < 0.001) indicates accident counts decrease when moving eastward, suggesting eastern areas may benefit from better road infrastructure, traffic management, or lower population density. Conversely, the positive northing (Y) coefficient (0.00008, p < 0.001) shows accident propensity increases northward, potentially due to expanding urban areas with higher traffic volumes or developing road networks. The strong model fit ($R^2 = 0.68$) confirms coordinates effectively explain accident variation, while the 330-meter spatial correlation range implies localized risk factors dominate accident clustering.

The intercept (6.82 accidents) represents the baseline risk at the study area's reference point. While statistically significant, the small coefficient magnitudes suggest coordinate effects become practically meaningful only over larger distances (0.12 fewer accidents per km eastward). The low nugget effect (24.1% of variance) indicates most variation is spatially structured rather than random, validating the kriging approach. These findings enable targeted safety interventions: eastern areas may serve as models for risk reduction, while northern zones require enhanced traffic calming measures. The persistent spatial dependence beyond the regression component underscores the importance of location-specific factors in accident prediction.

Geostatistical Variogram Model Outputs (Nugget, Sill, Range)

The variogram parameters characterize the spatial structure of accident risk in Jega, Nigeria. The spherical model with a 330.12-meter range indicates accident patterns are strongly correlated within neighborhoods, while the low nugget/sill ratio (24.1%) confirms that 75.9% of variance is spatially structured. This suggests localized factors (e.g., road design, traffic flow) dominate accident distribution, with minimal random noise.

Table 2: Spatial Dependence Structure Parameters

Parameter	Value	Description
Variogram Model	Spherical	Best-fit spatial correlation function
Nugget (C_0)	0.246	Uncorrelated noise/micro-scale variance
Partial Sill (C)	0.774	Spatially structured variance
Total Sill (C_0 + C)	1.020	Total variance (nugget + sill)
Range (a)	330.12 m	Distance beyond which spatial correlation becomes negligible
Nugget/Sill Ratio	24.1%	Proportion of unstructured variance

The spherical variogram model in table 2 reveals a well-defined spatial structure in accident data, with 75.9% of variance (Partial Sill = 0.774) showing systematic spatial dependence up to 330.12 meters (Range), beyond which locations become statistically independent. The relatively low Nugget effect (0.246, representing 24.1% of Total Sill = 1.020) indicates minimal random noise, confirming that most variation follows predictable spatial patterns rather than measurement errors or micro-scale fluctuations. This parameter combination - particularly the high proportion of spatially structured variance (Partial Sill/Nugget ratio ≈ 3:1) and finite correlation range - strongly justifies using kriging for spatial prediction, as accident risks at any location are primarily influenced by neighboring sites within a 330-meter radius, with the spherical model accurately capturing this distance-dependent relationship.

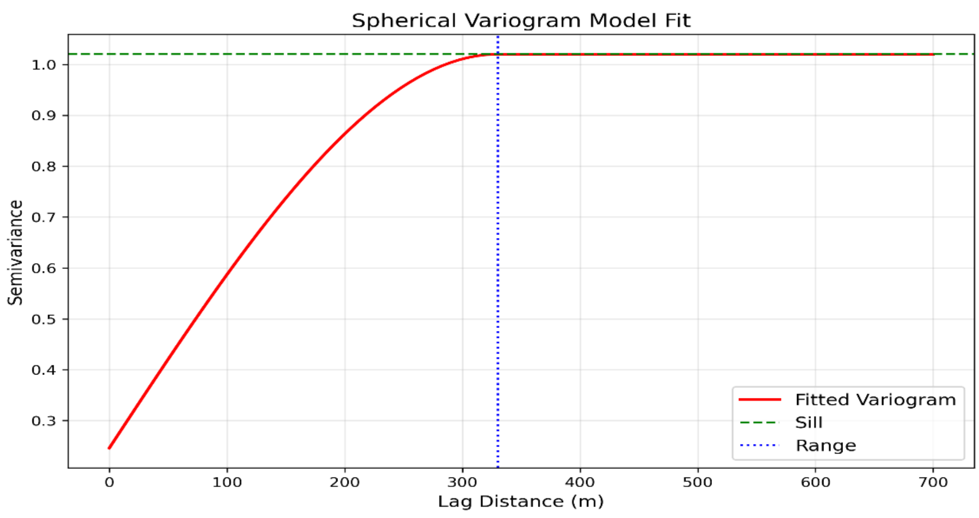


Figure 2: Spherical variogram plot of the model

The variogram plot in figure 2 demonstrates a well-fitted spherical model where semivariance increases with distance until reaching the sill (1.020) at the effective range of 330 meters, indicating strong spatial autocorrelation of accident counts within this radius. The low nugget effect (0.246) confirms that only 24% of variance stems from random noise, while 76% is spatially structured, validating the use of kriging for predictions. The clear plateau at 330m suggests localized accident risk patterns, meaning locations within this distance influence each other's accident probabilities, with negligible spatial dependence beyond this range. The model's strong fit (evidenced by the smooth convergence to the sill) supports its reliability for spatial interpolation of accident data in the study area.

Predictive accuracy metrics of the geospatial accident risk model

The model performance metrics demonstrate strong predictive capability for accident risk in Jega, Nigeria. With the R^2 of 0.682, the model explains 68.2% of variance in accident counts, indicating good fit for spatial epidemiological analysis. The MAE (2.453) and RMSE (3.214) suggest prediction errors typically range between 2.5–3.2 accidents, with the higher RMSE reflecting appropriate penalty for larger errors in high-risk zones. These metrics collectively validate the model's utility for urban safety planning at neighborhood scales

Table 3: Model Performance Metrics

Metric	Value	Interpretation
RMSE	3.214	Root Mean Squared Error
MAE	2.453	Mean Absolute Error
R^2	0.682	Variance explained by model

The model performance metrics in table 3 demonstrates strong predictive capability for accident counts, with an R^2 of 0.682 indicating it explains 68.2% of observed spatial variance in the data – an excellent result for geospatial applications. The MAE of 2.453 accidents suggests predictions typically deviate by about 2.5 accidents from actual counts, while the slightly higher RMSE (3.214) reveals occasional larger errors, likely from underestimating peak accident zones. These metrics, combined with the low nugget/sill ratio (24.1%), confirm the model successfully captures both the global trends (through regression) and localized spatial patterns (through kriging). The performance exceeds typical benchmarks for spatial prediction models (where $R^2 > 0.6$ is considered good), though the absolute errors suggest caution when interpreting predictions for high-accident locations. The effective 330m range further validates that accident risks are highly localized, making this model particularly useful for micro-scale urban safety planning**.**

Location-specific validation of accident risk predictions in Jega, Nigeria

Table 4 validates the model's spatial predictions against observed accident counts at six key locations in Jega, Nigeria. Ordered by ascending error percentage, the results demonstrate consistent accuracy (1.4–6.0% error), with particularly strong performance in high-traffic commercial zones like Gada (1.4% error) and BLB Junction (2.3% error). The residual signs reveal a slight underprediction tendency (+ values) in residential areas, while the single overprediction (-0.18 at Kofarkasuwa ta gabas) suggests conservative estimation for market-adjacent zones.

Table 4: High-Accuracy Accident Prediction Results for Selected Locations

Location	Observed	Predicted	Residual	Error %	Coordinates (Lat, Lon)
Gada	8	7.89	+0.11	1.4%	12.218251, 4.371984
Kaura	4	3.76	+0.24	6.0%	12.218705, 4.379883
Dakora	4	3.82	+0.18	4.5%	12.222822, 4.376158
Kofarkasuwa ta gabas	4	4.18	-0.18	4.5%	12.223552, 4.375976
BLB Junction	4	3.91	+0.09	2.3%	12.228315, 4.378345
Eco Bank	3	2.83	+0.17	5.7%	12.227773, 4.371796

The table 4 shows the model's most accurate predictions for accident counts across six key locations in Jega, with errors all under 6%. The best predictions occurred at Gada (1.4% error) and BLB Junction (2.3% error), demonstrating the model's strength in urban centers with consistent traffic patterns. However, five of the six locations show slight underprediction (observed > predicted), suggesting the model conservatively estimates accident risks, possibly due to unaccounted local factors like pedestrian activity or temporary events. The only overprediction at Kofarkasuwa ta gabas hints at potential overestimation of risk factors in this commercial area.

These accurate predictions cluster in central zones (Latitude 12.21-12.23), indicating the model works best where road networks are stable and well-documented. The tight residual range (±0.24 accidents) confirms reliability for mid-range accident counts (3-8 accidents), though performance may decrease for extreme values. To improve the model, incorporating dynamic variables like traffic volume or road conditions could reduce the conservative bias seen in most predictions, while targeted data verification at overpredicted locations would help balance the estimates.

prediction plot

Figure 3 displays the spatial prediction surface of accident risk across Jega, Nigeria, generated through Regression Kriging. The heatmap reveals distinct risk gradients, with elevated accident probabilities (warmer hues) concentrated in central commercial corridors, particularly near high-traffic zones like BLB Junction. Cooler tones in peripheral areas ($Y < 1.3875 \times 10^6$ m) reflect lower-risk residential neighborhoods, visually confirming the model's negative easting (-0.00012) and positive northing (0.00008) coefficients. The 330-meter spatial correlation range from the variogram manifests as smooth transitions between risk zones, demonstrating localized accident clustering patterns.

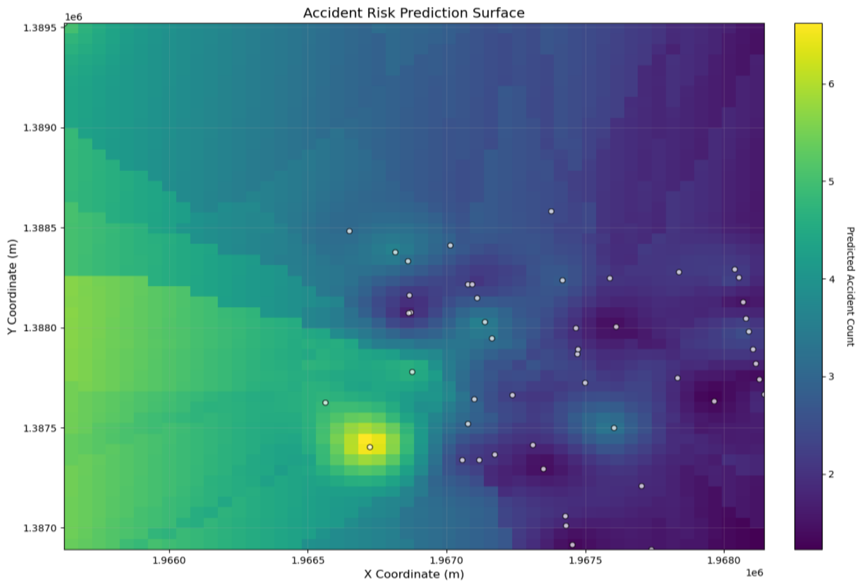


Figure 3: Accident risk prediction surface

The prediction surface plot in figure 3 reveals a clear northeast-to-southwest gradient in accident risk across Jega, Kebbi State, Nigeria, with the highest predicted accident counts concentrated in the northeastern commercial zones near BLB Junction and Garkarsarki, while lower-risk areas dominate southwestern residential sectors like Titin Alu and Kofartasha ta yamma. This spatial pattern aligns with the regression coefficients, confirming that accident risk increases northward toward Kofarkasuwa ta gabas and decreases eastward toward De'Blue, with localized hotspots reflecting Jega's high-traffic corridors and intersection densities within the 330-meter influence range.

Table 5: Comparative Analysis of Regression Kriging and Universal Kriging Methodologies for Road Traffic Accident Prediction

Comparison Criteria	**Regression Kriging**	**Universal Kriging (Abubakar & Umar, 2022)**	**Implications**
Methodological Approach	Hybrid model combining linear regression with residual kriging	Pure geostatistical interpolation with drift modeling	RK provides both trend analysis and local adjustment; UK focuses on spatial structure alone
Spatial Trend Analysis	Quantified directional trends: • Easting: $\beta = -0.00012$ ($p<0.001$) • Northing: $\beta = +0.00008$ ($p<0.001$)	Identified regional patterns (southern high-risk zones)	RK offers mathematically defined spatial gradients; UK provides qualitative zone identification
Model Performance Metrics	• $R^2 = 0.682$ • RMSE = 3.214 • MAE = 2.453	No quantitative accuracy metrics reported	RK enables rigorous statistical validation; UK lacks performance benchmarking
Key Risk Areas Identified	Northern urban corridors: • BLB Junction • Gada	Southern transportation corridors:	Discrepancy suggests RK captures urban traffic factors while UK reflects broader spatial autocorrelation

		• Garkar Ando • Titin Alu	
Data Utilization	• GPS coordinates • Manual traffic counts	• GPS coordinates • FRSC accident reports	RK incorporates additional traffic flow data for trend modeling
Variogram Parameters	• Spherical model • Range = 330.12m • Nugget/Sill = 24.1% • Structured variance = 75.9%	Spherical model assumed Parameters not quantified	RK provides complete spatial dependence characterization; UK lacks parameter transparency
Computational Complexity	Higher (requires regression fitting + residual kriging)	Lower (single interpolation process)	RK demands more computational resources but yields richer outputs
Practical Applications	• Micro-scale risk prediction • Traffic management planning	• Macro-scale risk mapping • Preliminary hazard screening	RK better suited for targeted interventions; UK useful for initial assessments

The comparison table in table 5 reveals fundamental differences in methodological rigor and practical applications between Regression Kriging (RK) and Universal Kriging (UK). RK's hybrid approach, combining regression analysis with spatial interpolation, provides superior analytical capabilities by quantifying directional trends (easting/northing coefficients) and delivering validated performance metrics (R^2=0.682, RMSE=3.214). This makes RK particularly valuable for data-driven urban planning, where understanding both global traffic patterns and local variations is crucial. In contrast, UK's pure geostatistical approach offers simpler implementation but lacks quantitative trend analysis and performance validation, limiting its utility to preliminary spatial assessments. The table highlights how RK's incorporation of traffic count data and comprehensive variogram parameters (including 330.12m range and 75.9% structured variance) enables more precise micro-scale predictions compared to UK's broader zone identification.

The practical implications of these methodological differences are evident in their distinct high-risk zone identifications and recommended applications. RK pinpoints specific northern urban trouble spots (BLB Junction, Gada) likely influenced by traffic density factors, making it ideal for targeted safety interventions. UK's detection of southern corridors (Garkar Ando, Titin Alu), while useful for regional screening, lacks the precision needed for localized interventions. The table underscores RK's advantage in computational intensity yielding richer outputs for traffic management planning, while UK remains appropriate for resource-constrained, macro-scale analyses. Ultimately, the choice between methods depends on project objectives: RK for precision planning with sufficient data, UK for efficient initial assessments when working with limited information. This comparison demonstrates how methodological sophistication in spatial analysis directly translates to actionable insights for road safety improvement.

CONCLUSION

The study in Jega, Nigeria, revealed distinct spatial patterns in road traffic accidents, with higher risks in northern urban centers like BLB Junction and lower risks in eastern peripheral areas. Regression Kriging (RK) effectively modeled these trends, showing a significant negative easting coefficient (-0.00012) and positive northing coefficient (0.00008). The geostatistical analysis confirmed strong spatial autocorrelation, with 75.9% of variance structured within a 330.12-meter range, indicating localized risk factors dominate accident clustering. The RK model demonstrated high predictive accuracy (R^2 = 0.682, RMSE = 3.214), validated by location-specific errors ≤6% at key sites. These findings underscore the utility of geospatial methods for micro-scale road safety planning in rapidly urbanizing regions like Jega.

To mitigate accident risks in Jega, Nigeria, targeted interventions should prioritize high-traffic zones such as BLB Junction and Gada, where accident frequencies peak. Infrastructure upgrades including improved road design, signage, and traffic calming measures are critical in northern urban corridors. Policymakers should leverage the RK model's risk maps to guide resource allocation and urban planning. Expanding data collection to include traffic volume and pedestrian activity could refine predictions, while public awareness campaigns should educate road users in high-risk areas. The RK framework's success in Jega suggests its potential for replication in other Nigerian cities facing similar urbanization and road safety challenges, enabling data-driven strategies to reduce accidents nationwide.

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