SPATIAL CRIME PREDICTION USING POISSON REGRESSION KRIGING: A CASE STUDY FROM NIGER REPUBLIC

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ABSTRACT

This study applies Poisson Regression Kriging (PRK) to model and predict crime rates across a spatial region (Niger Republic), with particular attention to areas lacking direct observations. As crime data typically involve count variables, PRK is well-suited because it integrates a Poisson generalized linear model with kriging-based spatial interpolation of residuals. It was observed that literate rate (Z2), Education level (Z4) and population size (5) are key predictors, exerting a significant influence on most of the crimes (theft, narcotics, and abuse of confidence). By leveraging spatial dependence through kriging, PRK enables joint spatial prediction at unmonitored locations, generating a continuous prediction surface across the study area. This capability is critical for crime mapping, allowing for proactive decision-making in regions without historical crime records. The study also demonstrates the ability of PRK to generate accurate crime risk maps, identify hotspot zones (Tassara, Tibiri, and Malbaza), and guide data-driven policy decisions. Overall, the results confirm that PRK is an effective tool for spatial modeling of crime data, offering enhanced predictive accuracy and robust estimation in bunobserved zones.

Keywords: Niger Republic, Crime**,** Variogram, Poisson regression kriging

1. INTRODUCTION

The rise in crime incidents across various regions of the Niger Republic poses a serious threat to national stability, economic development, and public safety. The spatially uneven nature of these incidents, which is shaped by socio-economic, demographic, and geographic factors, necessitates the use of advanced spatial analysis tools to understand, monitor, and predict criminal activity.

The Republic of Niger, situated within the fragile Sahel region, is experiencing a growing security crisis exacerbated by a complex mix of armed insurgencies, transnational banditry, illicit trafficking, and socio-economic instability. Despite multiple interventions by both the national government and international actors, the crime rate continues to escalate, undermining peace, development, and institutional trust. Justice sector records indicate a near doubling of criminal offenses between 2014 and 2019, with rural and border communities increasingly vulnerable to attacks, displacement, and social disintegration.

The demographic structure of Niger, with a fast-growing population that is both highly dispersed and partially nomadic, complicates service delivery and exacerbates insecurity in underserved regions. The persistence of organized crime, particularly in areas such as Tillabéri, Maradi, and Tahoua, poses direct threats to national cohesion, economic activity, and public safety. Yet, while the threat is clear, analytical tools to understand the spatial and structural patterns of crime remain underutilized.

The application of geostatistical models to crime analysis has gained increasing attention in recent decades; however, their use in sub-Saharan Africa, and particularly in Niger, remains limited. Most existing studies on crime distribution and spatial modeling have focused on developed or data-rich countries, where detailed spatial and socio-economic datasets are readily available. Research such as Kerry et al. (2010, 2016) and Usman et al. (2021) has demonstrated the effectiveness of geostatistical techniques in other contexts, yet their methodological frameworks have not been fully adapted to regions characterized by data scarcity, spatial heterogeneity, and inconsistent reporting. Consequently, the empirical understanding of spatial crime dynamics in Niger remains fragmented and underexplored.

Traditional approaches to crime modeling, including ordinary least squares (OLS) or multiple regression models, often fail to capture the spatial autocorrelation inherent in crime data and the count-based structure of crime events. These models assume independence of observations and normally distributed errors, assumptions that are rarely met in spatial criminological data. As a result, their predictive performance and interpretability are limited when applied to geographically dependent or discrete crime data. Several studies have highlighted the importance of integrating spatial components into crime modeling (Anselin et al., 2000; Bernasco & Steenbeek, 2017), yet few have developed robust frameworks that accommodate both spatial dependence and count-based variability simultaneously.

To address this methodological gap, the present study employs Poisson Regression Kriging (PRK), an advanced geostatistical approach that integrates Poisson regression for modeling the discrete nature of crime counts with kriging of residuals, which captures the spatial autocorrelation structure. This hybrid method not only improves prediction accuracy but also enhances the interpretability of spatial crime patterns. The empirical variogram plays a central role in quantifying spatial dependence and guiding the selection of appropriate kriging parameters. By combining these methodological elements, PRK produces smoothed, data-driven crime risk maps that better reflect the spatial continuity of criminal activity.

By adapting this model to the Nigerien context, the study extends the frontier of geostatistical applications in criminology and provides a replicable methodological framework for similar socio-geographic environments. This contribution is particularly valuable for regions facing data constraints, as it promotes evidence-based decision-making, resource allocation, and the formulation of spatially informed public safety policies.

In crime analysis, RK allows for the incorporation of auxiliary variables such as population density, unemployment rates, or road accessibility while accounting for spatial autocorrelation in residuals (Hengl et al., 2007). This method has been applied in environmental and socio-economic contexts (Goovaerts, 2000 ; Tatem et al., 2013), with growing adoption in criminology and urban planning.

Crime data are typically recorded as counts, which makes traditional linear modeling inappropriate. Poisson regression and its variants are suitable alternatives as they naturally handle count distributions and incorporate covariates (Cameron & Trivedi, 2013). Generalized linear models (GLMs) with Poisson or negative binomial distributions have been widely used in crime research to explore the influence of socio-economic factors on crime incidence (Andresen, 2011 ; Kubrin & Herting, 2003; Montiel Olea et al., 2021).

Poisson kriging is a geostatistical method specifically designed for count data. It has been used effectively in epidemiology, ecology, and public health (Monestiez et al., 2006), and is increasingly explored for crime prediction. Poisson regression kriging (PRK) integrates Poisson regression modeling with spatial interpolation of residuals, enabling the generation of smoothed crime risk maps while respecting the discrete nature of crime data (Goovaerts, 2005). This approach is particularly useful in settings with sparse or unevenly distributed data such as the Niger republic where traditional methods may fail to capture underlying patterns. However, among these methods, only regression kriging was applied to crime data in Niger (Dodo et al., 2025) and Poisson regression kriging has not been applied to Niger's crime data.

This study aims to further improve the accuracy and interpretability of spatial predictions through the application of Poisson regression kriging models. This technique is particularly well-suited for discrete count data, such as the number of crime occurrences, and allows for a comprehensive spatial modeling framework that combines generalized linear modeling (GLM) with geostatistical interpolation. In Niger Republic, where crime data is often sparse or inconsistently reported, especially outside of major urban centers, this modeling approach offers a powerful tool for generating reliable estimates at unmonitored locations.

The ability to make joint spatial predictions is crucial for security agencies and decision-makers to deploy resources efficiently in underserved regions. Through the integration of covariate data like (population size, literacy rate, education level, unemployement rate, school attendance) and spatial autocorrelation captured via the variogram, Poisson regression kriging provides a statistically rigorous approach to extrapolate crime risks in areas with limited direct observation. By applying Poisson regression kriging methods, this study bridges an important methodological and contextual gap, offering an innovative geostatistical approach to Niger republic crime analysis that supports evidence-based policing and national security planning. The aim of this study is to analyse a spatial crime prediction in Niger Republic using Poisson regression kriging.

This study provides significant contributions to both policy formulation and academic research, particularly in the domain of spatial crime analysis in Niger. By applying advanced geostatistical techniques Poisson Regression Kriging (PRK), it offers a robust and innovative framework for understanding, predicting, and managing crime.

2. METHODOLOGY

Study area

Niger, a landlocked nation situated in West Africa, covers an area of 1,267,000 square kilometers. Geographically, it lies between latitudes 11°37' and 23°33' North, and longitudes 0°06' and 16° East of the prime meridian. The country is bordered to the north by Algeria and Libya, to the east by Chad, to the south by Nigeria and Benin, and to the west by Burkina Faso and Mali. It shares a total of 5,697 kilometers of borders with these neighboring countries: Chad (1,175 km), Nigeria (1,497 km), Algeria (956 km), Mali (821 km), Burkina Faso (628 km), Benin (266 km), and Libya (354 km). As per Law No. 2008-42 enacted on July 31, 2008, Niger is administratively organized into eight regions, which are subdivided into 66 departments and further into 265 municipalities (INS, 2020).

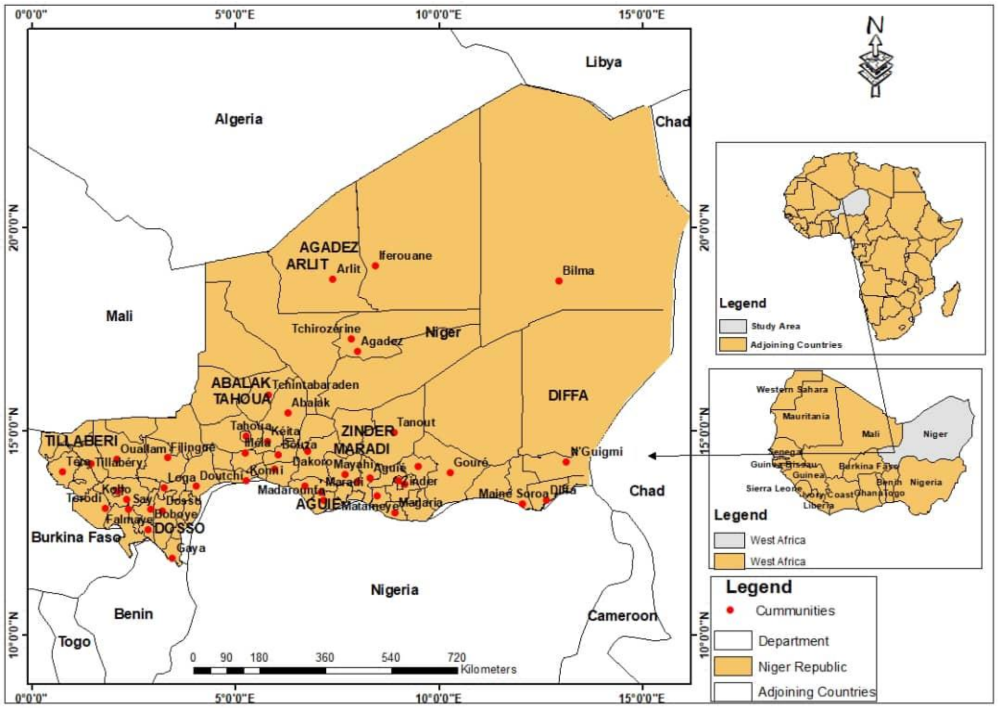

Figure 1: Map of Niger Republic

Data of the study

The data for this research is secondary and was sourced from the Statistics Directorate of the Ministry of Justice criminal records. It includes information from nearly all District and High Courts across the country, specifically concerning adjudicated cases those that have been heard and resolved with a judicial decision. The dataset includes variables such as origin of the crimes, covering the period from 2015 to 2022. Due to data limitations, the dataset consists of the following crime categories, cases of abuse of confidence, cases of criminal associations, cases of corruption, cases of illegal arms possession, cases of embezzlement, cases of fraud (419), cases of counterfeit money, cases of murder, cases of rebellion, cases of receiving stolen goods, cases of narcotics, cases of violence or assault, and cases of theft. Additionally, the dataset includes variables such as the unemployment rate, literacy rate, school attendance rate, educational level, and population size. The geographical coordinates of the District and High Courts, where each crime was adjudicated, were used as the locations for the crime analysis. R Studio, ArcGIS, and Excel software were used for data analysis.

Poisson model

The Poisson kriging is a geostatistical estimation method tailored for spatial count data, which are typically modelled as Poisson random variables. This method accounts for the inherent heteroscedasticity (variance depends on the mean) and spatial correlation of counts aggregated over supports of varying sizes (e.g., population or area).

Let

$Z(u_i)$: observed count at u_i location

$v(u_i)$: known population at u_i location

$\lambda(u_i)$: unknown Poisson rate at u_i (rate per unit support)

Assuming that the counts follow a Poisson distribution:

$$\mathrm{Z}(u_i) \sim Poisson\ \left(\lambda(u_i)\ \mathrm{v}(u_i)\right) \tag{1}$$

The $\lambda(u_i)$ and $v(u_i)$ represent the locality crime risk and the population size that are at risk at location u_i respectively. The goal is to estimate the unknown rate $\lambda(u_0)$ at an unsampled location u_0.

Estimator of the poisson model

Goovaerts (2005) gave a detailed description of the methodology of geostatistics or risk values estimation from empirical frequencies, and its performance relative to common smoothers. Haining, Kerry, and Oliver (2010) adapted kriging in the use of crime data and proceeded as follows. The number of recorded crime cases $Z(u_i)$ is interpreted as a realization of a random variable that follows a Poisson distribution with one parameter (expected number of crimes) that is the product of the population size $v(u_i)$ and the local crime risk $\lambda(u_i)$. The $\lambda(u_i)$ might be considered for area u_i as a crime rate noise-filtered, which is also referred to as the crime risk. The estimate value is obtained by the use of a variant of kriging with non-systematic errors, known as Poisson kriging (Monestiez et al., 2005). The Poisson kriging estimator is derived from the Ordinary Kriging estimator. The Poisson kriging crime risk is estimated as a linear combination of n neighbouring data.

The linear estimator was constructed as:

$$\hat{\lambda}_{PK}(u_0) = \sum_{i=1}^{n} w_i \frac{Z(u_i)}{v(u_i)} \tag{2}$$

Where w_i are weights to be determined and $\frac{Z(u_i)}{v(u_i)}$ represents the observed rate at location u_i that is the crime rate

Unbiasedness constraint

The estimator must be unbiased, which means: $E\left[\hat{\lambda}(u_0) - \lambda(u_0)\right] = 0$

Since $E\left[\frac{Z(u_i)}{v(u_i)}\right] = \lambda(u_i)$, this implies: $\sum_{i=1}^{n} w_i = 1$

Variance of estimation error

Define the estimation error as:

$$e(u_0)=\hat{\lambda}(u_0)-\lambda(u_0)=\sum_{i=1}^{n}w_i\frac{Z(u_i)}{v(u_i)}-\lambda(u_0) \tag{3}$$

The variance of this error is:

$$e(u_0)=\hat{\lambda}(u_0)-\lambda((u_0)=\sum_{i=1}^{n}w_i\frac{Z(u_i)}{v(u_i)}-\lambda(u_0) \tag{4}$$

$$\sigma_{PK}^2(u_0)=Var\left(e(u_0)\right) \tag{5}$$

$$=E\left[e(u_0)^2\right]-\left(E\left[e(u_0)\right]\right)^2$$

$$=E\left[e(u_0)^2\right]$$

Expending, we get:

$$\sigma_{PK}^2(u_0)=\sum_{i=1}^{n}\sum_{j=1}^{n}w_iw_jCov\left(\frac{Z(u_i)}{v(u_i)},\frac{Z(u_j)}{v(u_j)}\right)-2\sum_{i=1}^{n}w_iCov\left(\frac{Z(u_i)}{v(u_i)},\lambda(u_0)\right)+Var\left(\lambda(u_0)\right) \tag{6}$$

Covariance between observed rates

Since $Z(u_i)$ are Poisson count over support $v(u_i)$, their covariance is:

$$Cov\left(Z(u_i),Z(u_j)\right)=C\left(u_i,u_j\right).v(u_i)v\left(u_j\right)+\delta_{ij}\lambda(u_i)v(u_i) \tag{7}$$

Where: $C\left(u_i,u_j\right)$ is the covariance of the latent rate field $\lambda(u)$

δ_{ij} is the Kronecker delta.

Dividing both sides by $v(u_i)v\left(u_j\right)$:

$$Cov\left(\frac{Z(u_i)}{v(u_i)},\frac{Z(u_j)}{v(u_j)}\right)=C\left(u_i,u_j\right)+\delta_{ij}\frac{\lambda(u_i)}{v(u_i)} \tag{8}$$

Covariance between observed rate and target rate

Assuming stationarity:

$$Cov\left(\frac{Z(u_i)}{v(u_i)},\lambda(u_0)\right)=C\left(u_i,u_0\right) \tag{9}$$

Minimization of variance with constraint

Minimize $\sigma^2(u_0)$ subject to the constraint $\sum_{i=1}^{n} w_i = 1$

Use a Lagrange multiplier μ to form w_k and setting to zero:

$$L = \sigma^2(u_0) - 2\mu\left(\sum_{i=1}^{n} w_i - 1\right) \tag{10}$$

Taking derivatives with respect w_k to and setting to zero:

$$\frac{\partial L}{\partial w_k} = 2\sum_{j=1}^{n} w_j Cov\left(\frac{Z(u_k)}{v(u_k)}, \frac{Z(u_j)}{v(u_j)}\right) - 2Cov\left(\frac{Z(u_k)}{v(u_k)}, \lambda(u_0)\right) - 2\mu = 0 \tag{11}$$

Simplifying

$$\sum_{j=1}^{n} w_j Cov\left(\frac{Z(u_k)}{v(u_k)}, \frac{Z(u_j)}{v(u_j)}\right) + \mu = Cov\left(\frac{Z(u_k)}{v(u_k)}, \lambda(u_0)\right) \tag{12}$$

Final kriging system

Substituting the covariance expressions

$$\sum_{j=1}^{n} w_j\left(C(u_k, u_j) + \delta_{kj}\frac{\lambda(u_k)}{v(u_k)}\right) + \mu = C(u_k, u_0) \tag{13}$$

Or equivalently:

$$\sum_{j=1}^{n} w_j\left(\frac{1}{v(u_j)} C(u_k, u_j) + \delta_{kj}\frac{1}{v(u_j)}\right) + \mu = C(u_k, u_0) \tag{14}$$

With the constraint:

$$\sum_{j=1}^{n} w_j = 1$$

Poisson kriging estimator

The weight $\{w_i\}$ are found by solving the above system, and the estimate at u_0 is:

$$\hat{\lambda}(u_0) = \sum_{i=1}^{n} w_i \frac{Z(u_i)}{v(u_i)}$$

3. RESULTS AND DISCUSSION

Poisson kriging for the case of violence or assault

The table 1gives the summary statistics of the poisson regression kriging analysis results for violence or assault crime type.

Table 1: Summary statistics of violence or assault poisson regression kriging analysis.

Predictor	Estimate	Std. Error	t-value	p-value	Significance
Intercept	2.156	0.5796	3.720	0.000641	*** (Highly significant)
Z1	0.1004	0.09168	1.095	0.280410	Not significant
Z2	0.04204	0.01497	2.809	0.007813	** (Significant)
Z3	0.001706	0.006937	0.246	0.807048	Not significant
Z4	-0.02696	0.01327	-2.032	0.049165	* (Marginally significant)
Z5	2.143e-06	5.408e-07	3.963	0.000315	*** (Highly significant)

As shown in Table 1, the literacy rate (Z2, $p = 0.0078$) has a positive effect on violence/assault. In contrast, the educational level (Z4, $p = 0.0491$) demonstrates a negative influence. Additionally, the population level (Z5, $p = 0.0003$) has a strong positive impact on violence/assault. However, unemployment rate (Z1) and school attendance (Z3) ($p > 0.05$) do not exhibit any statistically significant effect.

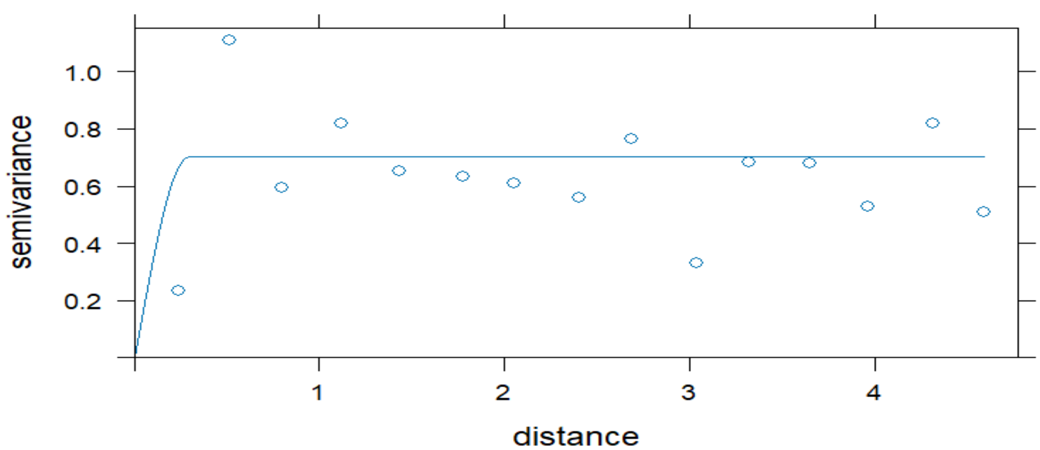

Figure 1: Kriging of the residual variogram of PRK violence or assault

The spherical model effectively captures the residuals of Poisson regression kriging. The absence of a nugget effect indicates a strong spatial structure with minimal measurement error. Additionally, the range of 0.2952 units Table 2 suggests that spatial correlation extends over this distance.

Table 2 : kriging residual variogram parameters PRK violence or assault cases

Model Type	Partial Sill (psill)	Range	Kappa
Nugget	0.0000000	0.0000000	0.0
Spherical (Sph)	0.7031	0.2952	0.5

Poisson regression kriging for the case of narcotic

The table 3 gives the summary statistics of the poisson regression kriging analysis results for narcotic crime type.

Table 3: Summary statistics of narcotic poisson regression kriging analysis.

Predictor	Estimate	Std. Error	t-value	p-value	Significance
Intercept	2.855	0.7788	3.666	0.00075	*** Highly Significant
Z1	0.1906	0.1232	1.547	0.13004	Not Significant
Z2	0.0530	0.0201	2.637	0.01204	* Significant
Z3	-0.0007	0.0093	-0.072	0.94337	Not Significant
Z4	-0.0180	0.0178	-1.010	0.31896	Not Significant
Z5	1.496e-06	7.267e-07	2.058	0.04648	* Significant

The Table 3 indicates an intercept which is highly significant ($p < 0.001$), indicating a strong baseline trend in narcotics cases. The literacy rate and population size respectively Z2 and Z5 ($p < 0.05$) are key predictors, exerting a significant influence on narcotics-related crimes. Conversely, unemployment rate, school attendance rate and educational level respectively Z1, Z3, and Z4 ($p > 0.05$) do not show a statistically significant impact on narcotics-related crimes.

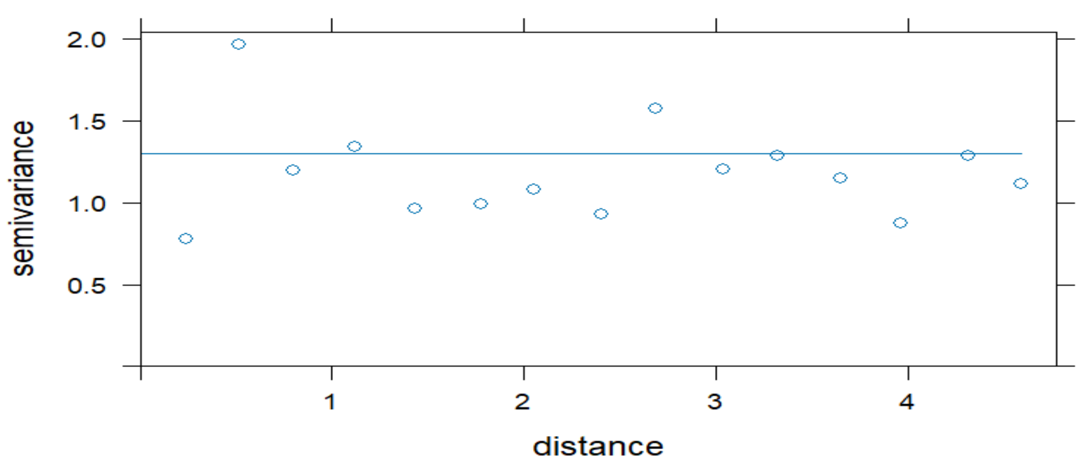

Figure 2: Kriging of the residual variogram of PRK for narcotic cases

As presented in Table 4, the high nugget effect (1.2986) indicates a significant level of unexplained local variability (randomness).

Table 4: Kriging residual variogram parameters of PRK narcotics

Model Type	Partial Sill (psill)	Range	Kappa
Nugget	1.2986	0.0000	0.0
Spherical (Sph)	0.0000	2000 units	0.5

The spherical model, with a range of approximately 2000 units, suggests strong long-range spatial clustering of narcotics-related crimes. Additionally, the zero partial sill implies a well-structured spatial dependence over extensive distances.

Poisson regression kriging for the case of recel

The table 11 gives the summary statistics of the poisson regression kriging analysis results for recel crime type.

Table 5: Summary statistics of recel Poisson regression kriging analysis.

Predictor	Estimate	Std. Error	t-value	p-value	Significance
Intercept	1.686	0.7460	2.261	0.02959	* Significant
Z1	0.1038	0.1180	0.880	0.38449	Not Significant
Z2	0.03819	0.01926	1.983	0.05468	Marginally Significant
Z3	-0.00942	0.00893	-1.056	0.29780	Not Significant
Z4	-0.02182	0.01707	-1.278	0.20898	Not Significant
Z5	2.445e-06	6.960e-07	3.513	0.00116	** Significant

The Table 5 shows that the intercept is significant ($p < 0.05$), suggesting a baseline trend in recel cases. The population size (Z5) shows high significance ($p = 0.00116$), indicating a strong influence on recel crimes. The literacy rate (Z2) is marginally significant ($p = 0.05468$), implying a weak effect on recel cases. In contrast, the unemployment rate (Z1), school attendance rate (Z3), and educational level (Z4) are not significant ($p > 0.05$), indicating no substantial impact.

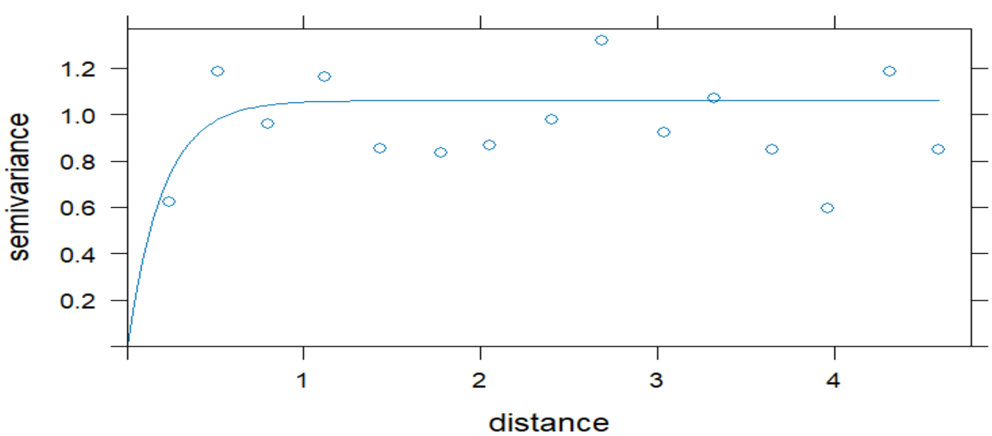

Figure 3: Kriging of the residual variogram of PRK for recel cases

A zero-nugget effect (0.0000) Table 6, signifies a well-organized spatial pattern with little randomness. The exponential model, with a range of 0.20 units, indicates that recel crimes are clustered in a very localized manner.

Table 6 : Kriging residuals variogram parameters of PRK recels cases

Model Type	Partial Sill (psill)	Range	Kappa
Nugget	0.0000	0.0000	0.0
Exponential (Exp)	1.0596	0.2004 units	0.5

Additionally, the high partial sill (1.0596) reflects a strong spatial dependence, though it occurs primarily over short distances.

Poisson regression kriging for the case of rebellion

The table 7 gives the summary statistics of the poisson regression kriging analysis results for rebellion crime type.

Table 7 : Summary statistics of rebellion poisson regression kriging analysis.

Predictor	Estimate	Std. Error	t-value	p-value	Significance
Intercept	0.5700	0.6206	0.918	0.364	Not Significant
Z1	-0.0141	0.0982	-0.144	0.887	Not Significant
Z2	0.02596	0.01602	1.620	0.114	Not Significant
Z3	0.00745	0.00743	1.003	0.322	Not Significant
Z4	-0.01432	0.01420	-1.008	0.320	Not Significant
Z5	8.259e-07	5.790e-07	1.426	0.162	Not Significant

The Table 7 indicates that none of the predictors (Z1 to Z5) are statistically significant ($p > 0.05$), indicating a lack of strong evidence for their influence on rebellion cases. Additionally, the intercept is not significant ($p = 0.364$), which suggests there is no baseline trend for rebellion cases.

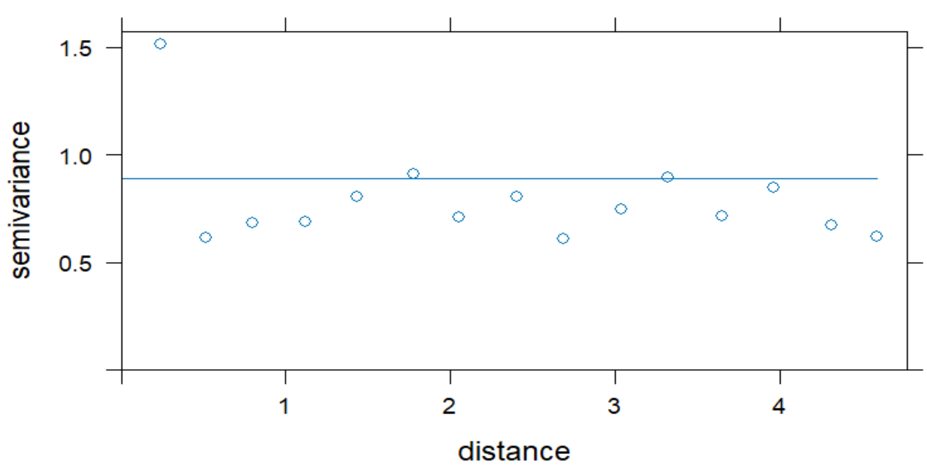

Figure 4: Kriging of the residual variogram of PRK for rebellion cases

The Table 8 shows a high nugget effect (0.8912) indicates a significant level of unexplained local variability (randomness).

Table 8 : Kriging residual variogram parameters of PRK for rebellion cases

Model Type	Partial Sill (psill)	Range	Kappa
Nugget	0.8912	0.0000	0.0
Spherical (Sph)	0.0000	2000 units	0.5

The Spherical model, with a range of 2000 units, implies a strong long-range spatial clustering of rebellion-related crimes. Additionally, the zero partial sill for the Spherical model suggests a structured spatial dependence over large distances.

Poisson regression kriging for the case of murder

The table 9 gives the summary statistics of the poisson regression kriging analysis results for murder crime type.

Table 9: Summary statistics of murder poisson regression kriging analysis.

Predictor	Estimate	Std. Error	t-value	p-value	Significance
Intercept	-1.257	0.1995	-6.300	2.21e-07	*** Highly Significant
Z1	0.0968	0.0316	3.068	0.00396	** Significant
Z2	0.0015	0.0052	0.299	0.76638	Not Significant
Z3	0.0055	0.0024	2.287	0.02788	* Significant
Z4	0.0117	0.0046	2.569	0.01424	* Significant
Z5	1.028e-06	1.862e-07	5.525	2.55e-06	*** Highly Significant

The intercept is highly significant ($p < 0.001$) as shown by the Table 9, indicating a strong baseline trend in murder cases. The unemployment rate (Z1), school attendance rate (Z3), educational level (Z4), and population size (Z5) are all statistically significant ($p < 0.05$), suggesting they have a strong influence on murder rates. In contrast, Z2 is not significant ($p > 0.05$), indicating it does not have a strong effect on murder rates.

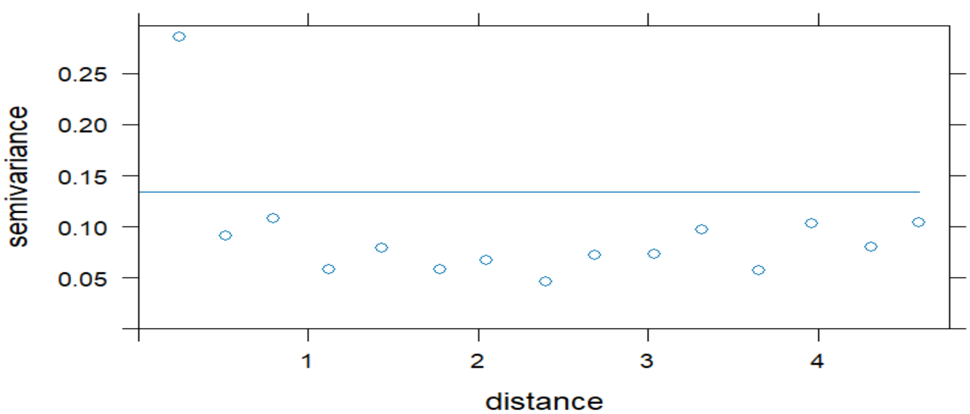

Figure 5: Kriging of the residual variogram of PRK for murder cases

The Table 10 shows a low nugget effect (0.1338) indicating minimal unexplained variability (randomness).

Table 10 : Kriging residual variogram parameters of PRK for murder cases

Model Type	Partial Sill (psill)	Range	Kappa
Nugget	0.1338	0.0000	0.0
Spherical (Sph)	0.0000	2000 units	0.5

The Spherical model, with a range of 2000 units, suggests long-range spatial clustering, indicating that murder cases are highly spatially dependent over large areas. Additionally, the zero partial sill for the Spherical model signifies strong structured spatial variation.

Poisson regression kriging for the case of counterfeit money

The table 11 gives the summary statistics of the poisson regression kriging analysis results for counterfeit money crime type.

Table 11 : Summary statistics of counterfeit money poisson regression kriging analysis.

Predictor	Estimate	Std. Error	t-value	p-value	Significance
Intercept	-0.005016	0.6863	-0.007	0.9942	Not significant
Z1	0.09444	0.1086	0.870	0.3898	Not significant
Z2	0.02556	0.01772	1.442	0.1574	Not significant
Z3	-0.01178	0.008213	-1.435	0.1595	Not significant
Z4	0.002199	0.01571	0.140	0.8894	Not significant
Z5	1.855e-06	6.403e-07	2.898	0.0062	** (Significant)

The Table 11, shows that only the population size (Z5) is statistically significant ($p = 0.0062$), indicating a strong influence on counterfeit money activity. The other variables unemployment rate (Z1), literacy rate (Z2), school attendance rate (Z3), and educational level (Z4) are not significant ($p > 0.05$), suggesting they do not have a substantial effect. Additionally, the intercept is not significant ($p = 0.9942$), indicating no inherent baseline trend.

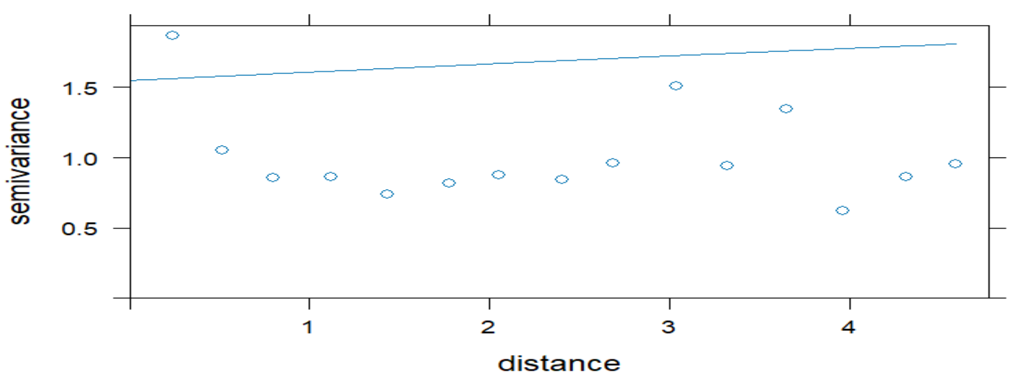

Figure 6: Kriging of the residual variogram of PRK for counterfeit money cases

The nugget effect (1.5484) reveals significant unexplained local variability. The spherical model, with a range of 11.5599, indicates spatial correlation extending up to 11.56 units, reflecting a strong spatial dependence.

Table 12 : Kriging residuals variogram parameters of PRK for counterfeit money cases

Model Type	Partial Sill (psill)	Range	Kappa
Nugget	1.5484	0.0000	0.0
Spherical (Sph)	0.4589	11.5599	0.5

The moderate partial sill (0.4589) implies that while there is some structured spatial variation, it is primarily influenced by local randomness.

Poisson regression kriging for the case of scam

The table 13 gives the summary statistics of the poisson regression kriging analysis results for scam crime type.

Table 13: Summary statistics of scam poisson regression kriging analysis.

Predictor	Estimate	Std. Error	t-value	p-value	Significance
Intercept	0.8691	0.6903	1.259	0.21570	Not Significant
Z1	0.1545	0.1092	1.415	0.16508	Not Significant
Z2	0.05827	0.01782	3.269	0.00229	Significant
Z3	-0.0062	0.0083	-0.752	0.45644	Not Significant
Z4	-0.0164	0.0158	-1.038	0.30583	Not Significant
Z5	2.276e-06	6.440e-07	3.534	0.00109	Significant

Table 13 shows that literacy rate and population size Z2 and Z5 are statistically significant ($p < 0.05$), indicating they have a substantial impact on scam-related crimes. In contrast, unemployment rate, school attendance and educational level respectively Z1, Z3, and Z4 are not significant ($p > 0.05$), suggesting they do not have a strong effect on scam cases. The intercept is also not significant, implying there is no inherent baseline trend in scam occurrences.

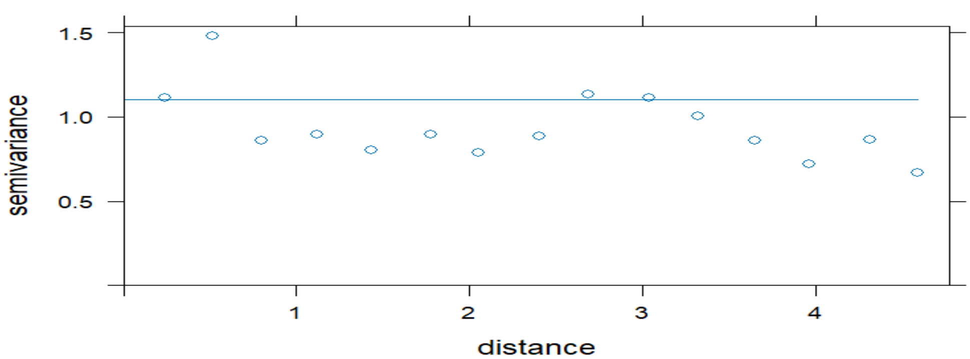

Figure 7: Kriging of the residual variogram of PRK for scam cases

The high nugget effect (1.10198) indicates significant unexplained local variability (randomness). The spherical model, with a range of 2000 units, points to strong long-range spatial clustering of scam cases.

Table 14 : Kriging residual variogram parameters of PRK for scam cases

Model Type	Partial Sill (psill)	Range	Kappa
Nugget	1.10198	0.0000	0.0
Spherical (Sph)	0.0000	2000 units	0.5

The zero partial sill for this model suggests a structured spatial dependence over extended distances.

Poisson regression kriging for the case of embezzlement

The table 15 gives the summary statistics of the poisson regression kriging analysis results for embezzlement crime type.

Table 15: Summary statistics of embezzlement poisson regression kriging analysis.

Predictor	Estimate	Std. Error	t-value	p-value	Significance
Intercept	0.6850	0.4201	1.631	0.1112	Not Significant
Z1	-0.0063	0.0664	-0.095	0.9248	Not Significant
Z2	0.0200	0.0109	1.845	0.0728	Marginally Significant
Z3	-0.0009	0.0050	-0.181	0.8573	Not Significant
Z4	-0.0168	0.0096	-1.752	0.0879	Marginally Significant
Z5	-1.184e-07	3.920e-07	-0.302	0.7643	Not Significant

The Table 15 shows that the literacy rate and educational level, represented by Z2 and Z4, are marginally significant ($p < 0.1$), suggesting they may have a weak influence on embezzlement cases. However, the unemployment rate, school attendance, and population size, represented by Z1, Z3, and Z5, are not significant ($p > 0.05$), indicating they do not have a strong effect. The intercept is also not significant, implying there is no baseline trend in embezzlement cases.

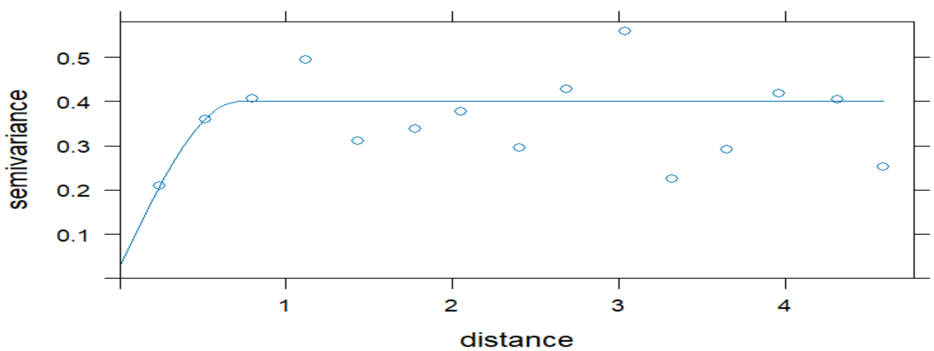

Figure 8: Kriging of the residual variogram of PRK for embezzlement cases

The low nugget effect (0.0298) indicates minimal unexplained local randomness.

Table 16 : Kriging Variogram parameters of PRK for embezzlmement cases

Model Type	Partial Sill (psill)	Range	Kappa
Nugget	0.0298	0.0000	0.0
Spherical (Sph)	0.3703	0.71 units	0.5

The spherical model, with a range of 0.71 units, points to localized spatial clustering of embezzlement cases. The moderate partial sill (0.3703) suggests the presence of structured spatial dependence.

Poisson regression kriging for the case of illegal arm possession

The table 17 gives the summary statistics of the poisson regression kriging analysis results for illegal arm possession crime type.

Table 17: Summary statistics of illegal arm possession Poisson regression kriging analysis.

Predictor	Estimate	Std. Error	t-value	p-value	Significance
Intercept	0.5551	0.6139	0.904	0.3716	Not Significant
Z1	0.2038	0.0971	2.099	0.0425	* Significant
Z2	0.0341	0.0159	2.151	0.0379	* Significant
Z3	-0.0031	0.0073	-0.415	0.6803	Not Significant
Z4	-0.0038	0.0141	-0.269	0.7892	Not Significant
Z5	2.536e-07	5.727e-07	0.443	0.6604	Not Significant

The Table 17 shows that the unemployment rate and literacy rate (Z1 and Z2) are statistically significant ($p < 0.05$), indicating they have a strong influence on illegal arms possession. However, school attendance rate, educational level, and population size (Z3, Z4, and Z5) are not significant ($p > 0.05$), suggesting they do not have a strong impact. The intercept is also not significant, meaning there is no inherent baseline trend in illegal arms possession cases.

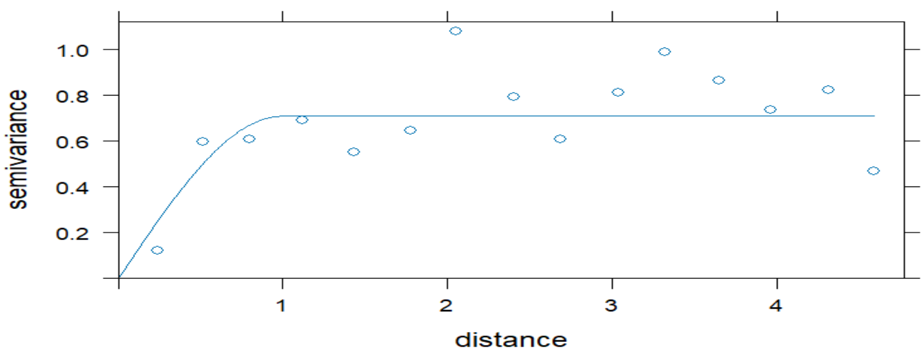

Figure 9: Kriging of the residual variogram of PRK for illegal arm possession cases

The absence of a nugget effect (0.0000) indicates a strong spatial structure with minimal randomness. The spherical model, with a range of 0.99 units, suggests short-range spatial clustering of illegal arms possession cases. The high partial sill (0.7100) indicates strong spatial dependence.

Table 18 : Kriging residual variogram parameters of PRK for illegal arm possession cases

Model Type	Partial Sill (psill)	Range	Kappa
Nugget	0.0000	0.0000	0.0
Spherical (Sph)	0.7100	0.99 units	0.5

Poisson regression kriging for the case of corruption

The table 19 gives the summary statistics of the poisson regression kriging analysis results for corruption crime type.

Table 19 : Summary statistics of corruption Poisson regression kriging analysis.

Predictor	Estimate	Std. Error	t-value	p-value	Significance
Intercept	-0.6454	0.3494	-1.847	0.0725	(Marginally significant)
Z1	0.01307	0.05526	0.236	0.8143	Not significant
Z2	0.01984	0.009021	2.199	0.0340	* (Significant)
Z3	-0.0003149	0.004181	-0.075	0.9404	Not significant

Z4	0.003672	0.007996	0.459	0.6487	Not significant
Z5	3.442e-07	3.260e-07	1.056	0.2977	Not significant

The Table 19 shows that the literacy rate (Z2) is positive and statistically significant (p = 0.0340), indicating it increases the likelihood of corruption. The intercept (p = 0.0725) is marginally significant, suggesting that baseline corruption levels may exist, but with weaker statistical confidence. The unemployment rate, school attendance rate, educational level, and population size (Z1, Z3, Z4, and Z5) are not significant (p > 0.05), meaning these variables do not have a strong influence on corruption.

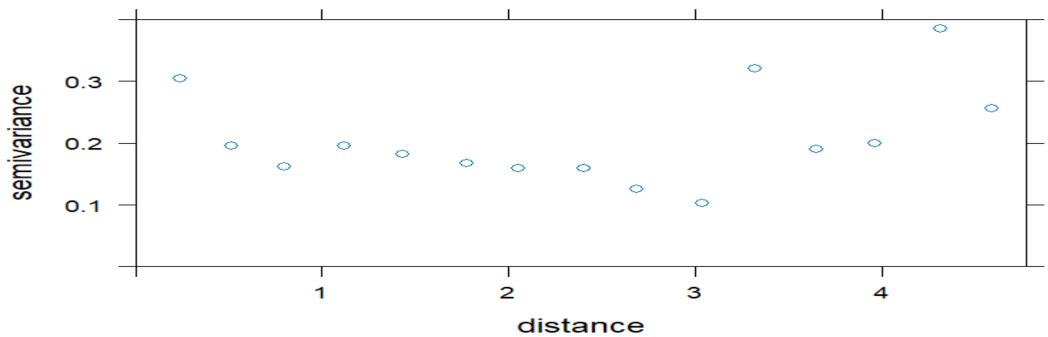

Figure 10 : Kriging of the residual variogram of PRK case of corruption cases

The nugget effect (0.4445) table 20, indicates some unexplained variation at very short distances, suggesting the presence of noise or small-scale variability. The spherical model, with a range of 1.5311, shows that spatial correlation extends up to 1.531 units, indicating broad spatial dependence. The absence of a partial sill for the spherical model suggests that, after accounting for the nugget effect, the spatial structure is weaker.

Table 20 : Kriging residual variogram parameters of PRK for corruption cases

Model Type	Partial Sill (psill)	Range	Kappa
Nugget	0.4445	0.0000	0.0
Spherical (Sph)	0.0000	1.5311	0.5

Poisson regression kriging for the case of association of criminals

The table 21 gives the summary statistics of the poisson regression kriging analysis results for association of criminals crime type.

Table 21 : Summary statistics of association of criminals Poisson regression kriging analysis.

Predictor	Estimate	Std. Error	t-value	p-value	Significance
Intercept	0.2875	0.6992	0.411	0.6832	Not Significant
Z1	0.0343	0.1106	0.310	0.7583	Not Significant
Z2	0.0195	0.0181	1.082	0.2863	Not Significant
Z3	-0.0057	0.0084	-0.677	0.5024	Not Significant
Z4	-0.0017	0.0160	-0.108	0.9143	Not Significant
Z5	1.210e-06	6.524e-07	1.854	0.0715	Marginally Significant

The Table 21 shows that population size (Z5) is marginally significant ($p = 0.0715$), indicating it may have a weak influence on criminal association. However, all other predictors (Z1 to Z4) are not significant ($p > 0.05$), suggesting they do not have a strong effect on criminal association. The intercept is not significant ($p = 0.6832$), implying there is no inherent baseline trend.

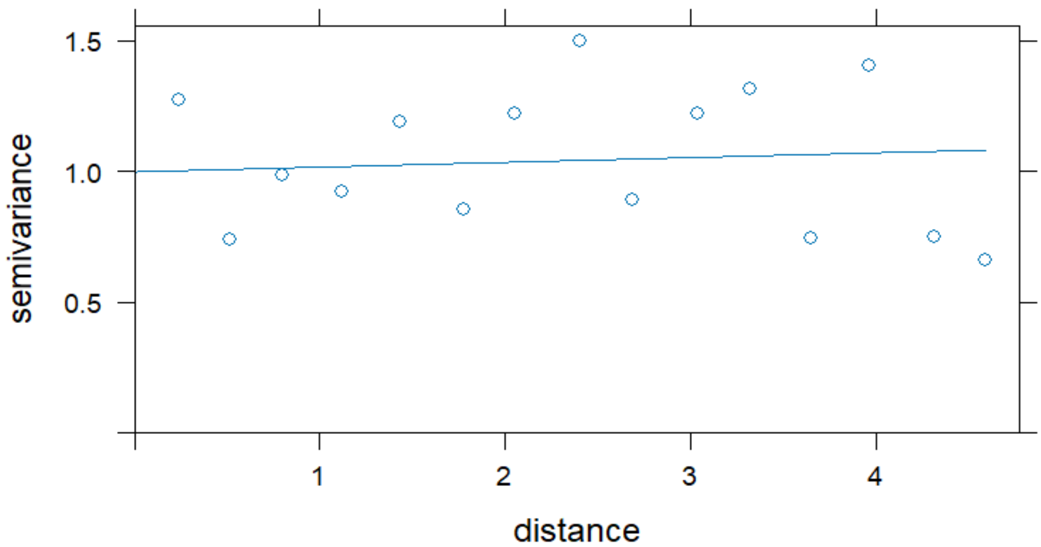

Figure 11: Kriging of the residual variogram of PRK for association of criminals cases

The Table 22 shows that, the high nugget effect (0.9981) indicates a significant amount of unexplained local variability (randomness). The spherical model, with a range of 40.17 units, suggests strong spatial correlation, meaning criminal association cases tend to cluster over large areas.

Table 22 : Kriging residuals variogram parameters PRK criminals associations cases

Model Type	Partial Sill (psill)	Range	Kappa
Nugget	0.9981	0.0000	0.0
Spherical (Sph)	0.4895	40.17 units	0.5

The moderate partial sill (0.4895) indicates some structured spatial variation, though it is still influenced by randomness.

Poisson regression kriging for the case of steal

The table 23 gives the summary statistics of the poisson regression kriging analysis results for steal crime type.

Table 23 : Summary statistics of steal poisson regression kriging analysis.

Predictor	Estimate	Std. Error	t-value	p-value	Significance
Intercept	4.538	0.7362	6.165	3.38e-07	*** Highly Significant
Z1	0.1356	0.1164	1.164	0.25158	Not Significant
Z2	0.05366	0.01901	2.823	0.00753	Significant
Z3	-0.00263	0.00881	-0.299	0.76689	Not Significant

Z4	-0.03409	0.01685	-2.023	0.05014	Marginally Significant
Z5	2.581e-06	6.868e-07	3.757	0.00058	*** Highly Significant

The Table 23 shows that the intercept is highly significant ($p < 0.001$), indicating a strong baseline trend in theft cases. The literacy rate (Z2) and population size (Z5) are statistically significant ($p < 0.05$), suggesting they have a strong influence on theft-related crimes. Educational level (Z4) is marginally significant ($p = 0.05014$), implying a weak influence on theft. Meanwhile, the unemployment rate (Z1) and school attendance (Z3) are not significant ($p > 0.05$), indicating no strong impact.

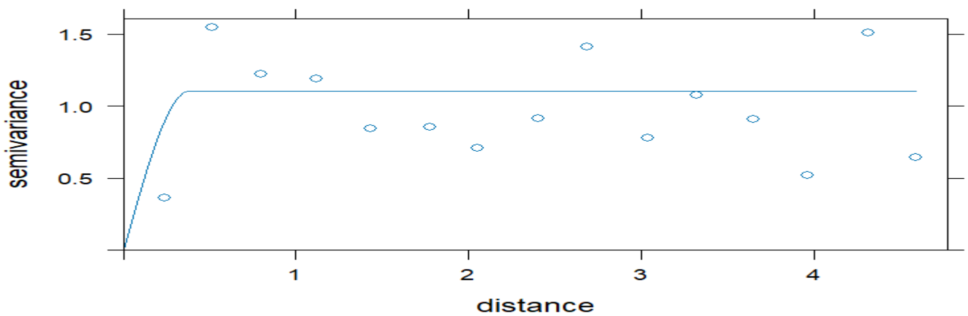

Figure 12: Kriging of the residual variogram of PRK case of steal

The zero-nugget effect (0.0000) Table 24, shows a well-structured spatial pattern with minimal randomness. The spherical model, with a range of 0.38 units, suggests that theft crimes exhibit localized spatial clustering.

Table 24 : Kriging residual variogram parameters PRK of steal cases

Model Type	Partial Sill (psill)	Range	Kappa
Nugget	0.0000	0.0000	0.0
Spherical (Sph)	1.10555	0.3835 units	0.5

The high partial sill (1.10555) indicates strong spatial dependence, though confined to short distances.

Poisson regression kriging for the case of abuse of confident

The table 25 gives the summary statistics of the poisson regression kriging analysis results for abuse of confident crime type.

Table 25 : Summary statistics of abuse of confident poisson regression kriging analysis.

Predictor	Estimate	Std. Error	t-value	p-value	Significance
Intercept	1.791	0.7767	2.306	0.02663	* (Marginally significant)
Z1	0.1312	0.1229	1.068	0.29240	Not significant
Z2	0.06329	0.02006	3.156	0.00313	** (Significant)
Z3	-0.003385	0.009295	-0.364	0.71775	Not significant
Z4	-0.02564	0.01778	-1.442	0.15750	Not significant
Z5	2.185e-06	7.247e-07	3.014	0.00457	** (Significant)

Table 25 shows that the literacy rate (Z2) is positive and significant (p = 0.0031), indicating it increases the likelihood of abuse of confidence. Population size (Z5) also has a strong positive effect (p = 0.0046), suggesting it plays a critical role. The intercept (p = 0.0266) is marginally significant, implying a baseline level of abuse of confidence. However, the unemployment rate (Z1), school attendance rate (Z3), and educational level (Z4) are not significant (p > 0.05), indicating they have little to no effect.

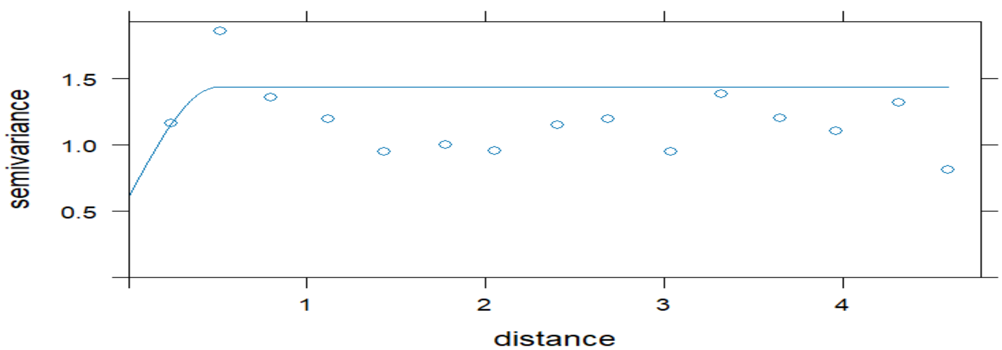

Figure 13: Kriging of the residual variogram of PRK for abuse of confidence cases

In the Table 26, The nugget effect (0.6159) suggests some unexplained variation at very short distances. The spherical model, with a partial sill of 0.8202 and a range of 0.5010, indicates that spatial correlation extends up to 0.501 units.

Table 26 : Kriging residual variogram parameters of PRK abuse of confidence cases

Model Type	Partial Sill	Range	Kappa
Nugget	0.6159	0.0000	0.0
Spherical (Sph)	0.8202	0.5010	0.5

This moderate spatial dependence suggests that abuse of confidence cases exhibit structured spatial clustering.

The table above, shows the predicted crime intensities for 18 unmonitored locations in Niger. The predictions are made for 14 crimes types, which includes high-impact crimes like *murder*, *narcotics*, *stealing*, and *violence/assault*. The values are continuous and represent expected crime rates based on the PRK model and can be interpreted as approximated counts per location.
Among the high-risk locations (major hotspot) we have Tassara (*Murder* (0.67), *Narcotic* (475.17), *Scam* (24.27), *Steal* (662.50), *Violence* (37.82)) ; Tibiri (*Abuse of confidence* (39.00), *Narcotic* (90.61), *Steal* (463.93), *Scam* (34.03)) and Malbaza and Tillia (Elevated narcotics, stealing, violence which suggests social vulnerability or porous borders). The low-risk locations concerns locations like Belbedji, Bankilare, Banibangou.

Location	**PRK prediction at unmonitored location**												
	Abuse of confidence	**Association of criminals**	**Corruption**	**counterfeit money**	**Embezzlement**	**Illegal arm possession**	**Murder**	**Narcotic**	**Rebellion**	**Recels**	**Scam**	**Steal**	**Violence or assault**
Ingall	21.2906848529237	1.36526154803963	0.109946992260795	1.64374999713466	1.02358899900267	4.75594127148496	-0.445145396211681	63.9135577599028	1.5063538388256	9.05153422155597	9.57199568498429	202.900750473966	15.4110592144913
Bosso	13.5029378713733	1.33728435680333	-0.1052790408868	0.787716690622375	0.750714197816324	3.21213497778044	-0.431530563715914	43.8387540949695	1.01300188124591	7.25323069715393	5.89756611727813	155.31291730114	12.4898020428861
Dioundou	21.1223712334859	1.5549719501251	0.254728449915001	2.37718915329431	0.988209403171684	4.93051451706565	-0.311130268215771	60.3316671465767	1.39871594630584	9.24318880914524	10.4980970647414	181.762235285562	14.0202669254053
Tibiri	39.0003208678993	2.87212121539236	0.367866300896995	3.99100806302091	1.06765079728693	1.88884189030057	-0.150151683461485	90.6142103696909	2.99093412014669	34.0339624346697	16.4850381246488	463.927102999828	13.7195734578904
Bermo	8.58411696367812	0.724080690738669	-0.264671231702022	0.43316468621345	0.858107842036047	2.41997319900351	-0.605368886611129	26.7321658465078	1.31488646912704	5.50886979717965	3.20854390812167	115.914054831294	9.68139875957342
Gazaoua	13.6583870691146	1.93618427295895	0.0410564308433861	2.30324441052356	0.335044919518575	1.30869143700872	-0.355569034524748	42.588775505879	2.42328053235285	6.24616290971954	7.40948640156629	160.367194674823	12.8847824850696
Malbaza	25.3034138331967	1.79938065577991	0.133824606416395	3.32944722647845	1.5366318776238	1.62036632239702	-0.0320236934073921	104.131145517774	1.01201361476787	15.7091789092032	14.566185106592	266.111667064987	18.7967360290145

Tassara	85.5778788813608	2.44084093316173	0.553856126696662	6.16467757498204	0.760597366702833	51.6785631394551	0.668700709949563	475.166778314208	1.04991007346349	24.2673533546221	55.4766557645119	662.498895401585	37.823251852125
Tillia	25.4846280591628	1.11302250031911	-0.0593489320610807	1.79903951338521	0.789100286602745	11.0411675521779	-0.189405868502831	110.456046302038	0.755013996697565	12.254920818836	13.1477179785588	285.871506168103	19.5712889464764
Banibangou	9.14845461798375	0.243681065505745	-0.162335346164053	-0.111574992078207	0.619177840482802	2.39281007906992	-0.245322100843413	36.3706335281499	1.50660693400375	3.47865678342178	3.22780276634141	114.63713338839	11.9367821110257
Bankilare	8.09585730777947	0.103883754103561	-0.317343926992903	-0.295743095309186	0.8304814654088	1.07456579889532	-0.370560340853062	29.8167983740292	1.5136430210848	3.53577814128474	2.32425386862176	127.287366730275	13.4231641775885
Gotheye	15.8090682754768	0.766655812352273	0.0237494845869513	0.467227424716347	0.97964141204602	1.43398915289705	-0.00811319328023807	50.4415626983267	2.48764651559911	6.39799420504602	6.30988369415866	194.235646904347	19.5458758483304
Ayérou	9.12091567291279	0.27363804753218	-0.0857472571738611	-0.093575855798712	0.638363859533227	1.85519357028268	-0.247945836076335	34.650439108336	1.47047928671119	3.08528006844129	3.18045656049561	104.38853254469	11.1948024744696
Dungass	14.1868548085247	2.23269435843094	-0.161489765657757	3.3194596816745	0.521672737144022	2.08010689371177	-0.204390126212886	38.9760971534284	1.73400886002611	12.142676052234	7.11459549563707	202.972525736217	16.2632907706402
Takeita	10.2055518713973	1.45379020943309	-0.300986750651017	2.12948230430573	0.278762764215637	2.55335853862577	-0.278683320798248	46.0256238574177	1.06797156312396	14.9159100641874	3.45344713877662	138.117753572549	10.2795021620757
Belbedji	5.025811441413	0.80292782829	-0.37726	0.74922940367	0.41964065190	1.3586620564873	-0.530654	18.895238361	0.85952210150	4.5542203564	2.0014616020	80.740524764	6.9167975802

	7	9072	6056954748	7622	464	2	337734642	4639	6815	5419	4907	1253	8079
Aderbissinat	15.29485132181 2	1.18716233095907	-0.0808701433695123	1.27517405887021	0.992812927051013	3.6385361175878 3	-0.508474804873648	48.2500262422386	1.57699601506531	7.59155432574197	6.46488603563588	169.44095916805	13.2226775558404
N'gourti	11.9503529757696	1.14266786784302	-0.108004908406447	1.0549129540886	0.449737503484051	5.4816037170951 4	-0.226494648919196	51.7332235875884	0.418776498657435	6.5514832763358	6.17321844168447	132.59952114381	10.6530466438787

CONCLUSION

This study investigated spatial crime patterns across the Niger Republic using advanced geostatistical methods specifically Poisson Regression Kriging (PRK). By integrating socio-economic predictors with spatial autocorrelation structures, the research successfully modeled and predicted crime occurrences unmonitored locations. The PRK emerged as a more accurate and statistically efficient model for count-based crime data. Its ability to generate meaningful predictions in data-scarce regions makes it especially valuable in contexts like Niger, where crime reporting is often incomplete or geographically imbalanced. The joint spatial prediction capability of PRK provides critical insight into potential crime hotspots, enabling authorities to proactively allocate security resources and develop targeted interventions. In addition, the study highlights the methodological advantage of incorporating both covariates and spatial structure into crime modeling. Overall, the research contributes both to academic knowledge and practical policy, offering a replicable framework for spatial crime analysis in developing countries. It paves the way for more informed decision-making and enhances the role of geospatial intelligence in national security planning.

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