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EXPLORATIVE GEOSPATIAL ANALYSIS OF ROAD TRAFFIC FATALITIES IN NIGERIA FOR THE PERIOD 2005 – 2018

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ABSTRACT

Geospatial analysis of road traffic crashes seeks to identify or detect areas of road safety concerns. This paper adopted the number of fatalities per crash to mine for any underlying patterns in road traffic fatality rates in states in Nigeria for the period 2005 – 2018. Four temporal periods were used for the study: 2005-2018, 2005-2009, 2010-2014 and 2015-2018. These data sets were analyzed using the Moran's I and Getis-Ord statistics. The global Moran's I results showed that the periods 2005-2018, 2005-2009 and 2015-2018 had a cluster of fatality rates in Nigeria. Spatial distribution of rates for 2010-2014 were however random. Getis-Ord General G statistics also found cluster in 2005-2018 and 2015-2018 distributions but 2005-2009 and 2010-2014 had random distributions. Anselin's Moran's I statistics indicated significant positive spatial autocorrelation for road traffic fatality rates for Kwara and Kogi states (2005-2009), Yobe and Jigawa (2010-2014) and Katsina, Kano, Bauchi and Rivers (2005-2018) while Delta state showed significant negative spatial autocorrelation (2015-2018). Getis-Ord Gi* results detected that the region of significant fatality rates was in the northern states especially of Katsina, Yobe, Jigawa, Kano and Bauchi, which show up more frequently in the study periods. Rivers and Abia states showed up as cold spots. The results generate several opportunities for closer scrutiny of road traffic crash data, for policy and legislation formulation to mitigate road traffic fatalities.

Keywords: Geospatial, Getis-Ord, Moran's I, road traffic fatality rate, spatial autocorrelation

INTRODUCTION

Road traffic crashes (RTC) are among the world's leading causes of death. The World Health Organization (WHO, 2018) reported that approximately 1.35 million people die annually from RTC globally. Most of these people, invariably, are in developing countries of the world. According to WHO (2015) the less developed countries of South Asia, Africa and Latin America collectively accounted for more than 90% of global road traffic fatalities. Nigeria has one of the highest rates of road traffic fatalities (RTF) in the world, about 1,042 fatalities for every 100,000 vehicles compared to 15 and 17 deaths per 100,000 vehicles for United States and Britain, respectively (Onyemaechi & Ufoma, 2017). Records released by the Federal Road Safety Corps showed that between 1960 and 2017, Nigeria recorded 1,134,760 crashes which resulted in 356,082 deaths. This is unacceptably high.

Over the years, researchers have mined road traffic data to gain better insight and understanding into the nature of the road traffic crashes problem in Nigeria. Such insights would provide informed and firm bases for developing strategies that would be effective to address the problem. There is increasing evidence to show that many current RTC researchers favour the employment of geospatial techniques to examine the different ramifications of the RTC problem. This approach generally utilizes spatial and temporal dimensions of the crashes to discern hidden patterns in the data.

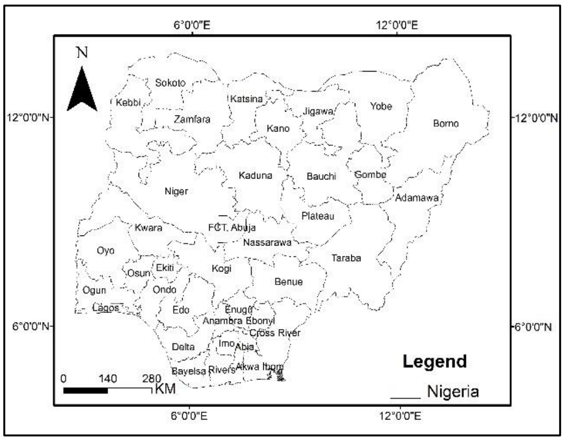
It is clear that road traffic crashes are spatial and temporal phenomena (Whitelegg, 1987). Spatially, each crash occurs at a given location, which may or may not (i.e., the location) have contributed to the crash itself. For example, it is common knowledge that road characteristics, such as sinuosity, curvature or grade are responsible for many road crashes and fatalities. These factors are location specific and therefore may be part of the spatial contributors to crashes. This forms the basis for the identification of crash blackspots or hot spots. Secondly, all crashes occur at a particular time. Time could be measured in terms of the hour of the day, the day of the week, week of the month, month of the year and/or season of the year or even a group of years as well. Both spatial and temporal dimensions therefore are important, which increases the appeal of the geospatial methodology.

There are two basic thrusts to the geospatial methodology: the employment of disaggregated or aggregated methods (Sengupta, Gayah & Donnell, 2021). When point-specific data on crash locations are available, disaggregated techniques may be employed to decipher any patterns in the distribution of crash locations. One of the most popular of these techniques is detection of crash blackspots (Erdogan, 2009). In the absence of such data, however, several forms of aggregation may be used including street or route level (Bombom & Edino, 2009), or an area unit such as states (Osayomi & Areola, 2015). The disaggregated method allows for local or location-based remedial measures to be deployed, while the aggregation method provides opportunities for much larger and holistic action to be taken in identified road safety-deficient areas. Some of these may include policy and legislation reformation. Another advantage of the areal unit analysis is the capacity to study regional differences that may be hidden in the data. It is necessary for devising preventive and remedial measures at a larger scale, with the potential for large scale reductions in road traffic crashes and fatalities. This study explores the road traffic crash data for significant disparities in fatalities in Nigeria using GIS capabilities. Most geospatial analyses of traffic crash data employ the traditional crash rates that use population or vehicle miles or number of registered vehicles as a standardization factor (Erdogan, 2009; Osayomi & Areola, 2015). This paper adopts the number of fatalities per recorded crash as road traffic fatality rate. This fatality rate has the potentials to highlight significant road safety deficit areas that require attention and shed new light, insight and perspective on the scandalously high RTF statistics in Nigeria, and what the implications are for road safety in Nigeria.

METHODS

Study design

Road traffic crash data were obtained from the Federal Road Safety Corps (FRSC) Headquarters, Abuja. The data were already spatially aggregated based on the thirty six states of Nigeria and the Federal Capital Territory, Abuja for the period 2005 to 2018. The state level is the most common spatial level of aggregation for RTC in Nigeria. Information provided include total number of crashes, number of fatal, serious and minor road crashes, number of persons killed (RTF) and injured (RTI), total number of casualty and number of people involved in the RTC.



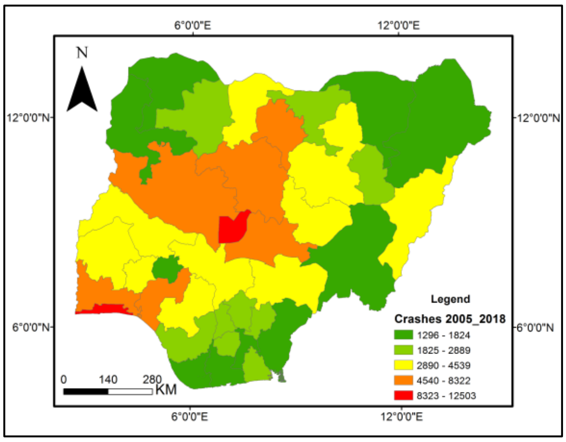


Figure 1: States of Nigeria and the FCT Figure 2: Total Number of Crashes 2005-2018

Though some studies have employed frequency data on RTC, RTF and RTI to analyze spatial patterns (Erdogan, 2008; Osayomi & Areola, 2015; Wang, Yi, Chen, Zhang and Qiang, 2021), many others use some forms of rates of RTC, RTF and RTI. This requires that the frequencies be normalized by some standard factor, the most popular being population, number of vehicle miles travelled (VMT) and number of registered vehicles (usually the rate is measured per 100,000 units of the standard factor, e.g. number of deaths per 100,000 persons or VMT). To calculate such a road traffic fatality rate, the following formula is used (Erdogan, 2009):

$$RTF\ (standardized\ by\ population) = \frac{(100{,}000 * number\ of\ fatalities)}{Total\ number\ of\ inhabitants} \quad (1)$$

This is a necessary step to normalize the frequencies by some standardized factor that would allow for comparisons between units of analysis, which have disparate characteristics.

Erdogan (2009), however, noted that the aforementioned commonly used rates are not true rates. For example, normalizing the frequency of RTC by population does not account for the fact that not all people that make up the population have the same exposure to RTC. While many people travel long distances every day to work and for other purposes, others travel very short distances or not all. Cars registered in one state may not even be used in that state, which means that the number of cars registered in a given state is not a true reflection of the number of cars in use in that state at any given time. Despite this concession, there is a general agreement that crash rates provide clear insights into hidden patterns inherent in RTC data and may resolve an important question as to whether the number of crashes recorded are 'inflated' or 'deflated' values based on other parameters of exposure to RTC risks.

This study adopts the number of RTC as the risk factor to normalize or standardize frequency of RTF in Nigeria. In each state, the frequency of RTF is divided by the number of RTC. First, this is a true rate. It measures the rate (and therefore risk) of death for every RTC recorded in the state, which is important because RTF only occurs when there is a RTC. Secondly, in more developed countries of the world, the RTF to RTC ratio is very low compared to those of developing countries such as Nigeria. This means that a higher frequency of RTC does not necessarily translate to a higher frequency of RTF. This may point to other contributory factors of RTF, such as the health of the vehicles, driving behavior and availability as well as accessibility to transportation and health infrastructure. Additionally, normalizing RTF by RTC is a simple but effective measure to explore any patterns of RTF at an aggregated level. This would allow for new perspectives to be developed, new hypotheses to be formulated and new insights into the relationship between RTC and RTF. All these are important to further the cause of prevention or mitigation of RTC and RTF in Nigeria.

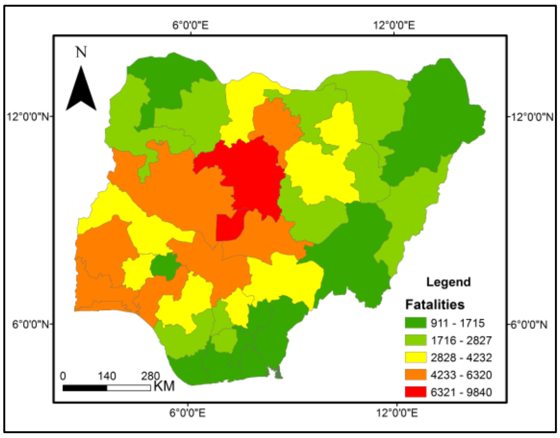


Figure 3: Number of Fatalities, 2005 – 2018

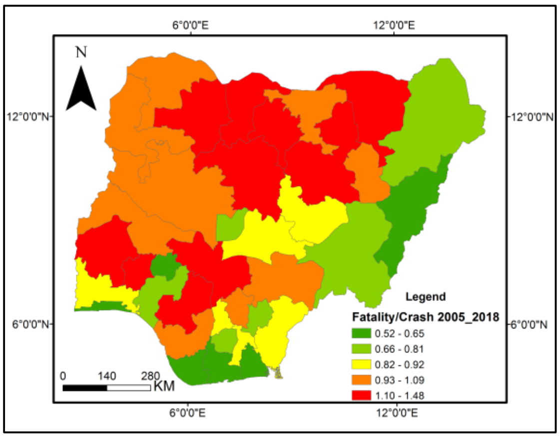


Figure 4: Fatality per Crash, 2005-2018

The study analyzed the data for the time period 2005 – 2018. It then decomposed the data into three temporal periods: 2005 – 2009; 2010 – 2014; and 2015 – 2018. ArcGIS 10.3 was the medium of data analysis. There are two groups of methods in ArcGIS to determine and measure strength of spatial clustering of aggregate areal data. These are global and local spatial autocorrelation methods.

Spatial autocorrelation

Spatial autocorrelation examines the extent to which a variable is correlated with itself. It is the concept captured as the First Law of Geography: 'Everything is related to everything else but near things are more related than distant things' (Tobler, 1970). If any systematic patterns of distribution exist for a given variable, it is said to be spatially autocorrelated. Neighboring areas with similar values of the variable are said to exhibit positive spatial autocorrelation irrespective of whether the values are positive or negative. Negative spatial autocorrelation therefore exists when an area of high or low values is surrounded by neighbors of dissimilar values. Random patterns show no spatial autocorrelations.

Spatial autocorrelation is important because crashes are not independent occurrences (Levine, Kim & Nitz, 1995; O'Sullivan & Unwin, 2003). Crashes are known to cluster along road segments and even in areas based on zonal characteristics, such as density of roads and cars, socio-economic activities, and population sizes among others. These characteristics exert a lot of influence on traffic generation and attraction, without which crashes would hardly occur.

There are several methods for calculating spatial autocorrelation. The Moran's Index and the Getis-Ord Index are two commonly used methods to analyze crash data (Erdogan, 2009; Osayomi and Areola, 2015). They are similar in many respects but have a fundamental difference. Both indices detect the presence of clusters of crashes (or other variables) in the distribution. Each polygon, referred to as a feature, has a value of the variable of interest (here, rate of fatalities). Each feature is surrounded by other features that share boundaries with it. Collectively, these features constitute a neighbourhood. The indices both calculate the average of the neighbourhood of each feature and assigns the value to it. Whereas Getis-Ord index computes the average based on the values of all features in the neighbourhood including the reference feature, the Moran's I index excludes the reference or core feature from the computation of the average of values of its neighbourhood. The identity of a feature as a hot spot therefore does not necessarily mean it has the highest values of the incident since it represents a neighbourhood rather than the feature alone and which differentiates the neighbourhood from others in the study area.

There are two basic forms of these models: global and local. The global model computes and returns only a single value, which determines whether the distribution of incidents is clustered. It is unable to identify the areas or locations where the variables are clustered or where spatial autocorrelation is significant (Nicholson, 1999). The global index is therefore limited in its output.

The global Moran's I global index is represented as:

$$I = \frac{N\sum_{i=1}^{N}\sum_{j=1}^{N} w_{ij}(X_i-\bar{X})(X_j-\bar{X})}{\left(\sum_{i\neq 1}^{N}\sum_{j=1}^{N} w_{ij}\right)\left(\sum_{i=1}(X_i-\bar{X})^2\right)} \qquad (2)$$

It has a range of values between -1 and +1 with -1 being perfect negative spatial autocorrelation and +1 representing the opposite extreme end of the spectrum, perfect positive spatial autocorrelation. Values around zero are indicative of random occurrences of incidents.

The Getis-Ord General G statistics, the global form of the model is represented as:

$$G = \frac{\sum_i\sum_j w_{ij}(X_iX_j)}{\sum_i\sum_j(X_iX_j)} \qquad (3)$$

When high values are clustered together, the General G statistics returns a high value, while low values indicate no clustering.

To detect location of clusters of values, measures of local spatial autocorrelation are developed. The major strength of local statistics lies in their flexibility and micro-level focus, which aid identification of the existence and nature of clustering and makes possible the delimitation and definition of objects (Getis & Ord, 1996).

For the Moran's model, the local indicator of spatial association (LISA) was developed by Anselin (1995). The mathematical form of the LISA is:

$$I_i = \frac{(X_i-\bar{X})}{S^2}\sum_j w_{ij}\left(X_j - X\right) \qquad (4)$$

LISA identifies four scenarios of clusters: first is high-high areas, which have areas of high values surrounded by neighbours of high values (positive spatial autocorrelation); high-low, which has an area of high value, surrounded by areas of low values (negative spatial autocorrelation); low-low, which has areas of low values surrounded by areas of low values as well (positive spatial autocorrelation); and low-high values, which means areas of low values are surrounded by neighbours with high values (negative spatial autocorrelation). Areas of negative spatial autocorrelation are referred to as outliers, while those of positive spatial autocorrelation are clusters.

Similarly, the Getis-Ord local model (G_i*) detects areas of spatial dependence. High values of G_i* show areas with clusters of high values. Which devate the most from a random istribution of the incidents, while low G_i* values identify areas with a cluster of low values. The G_i* is represented in the following formula:

$$G_i^* = \frac{\sum_j w_{ij}(d) x_j}{\sum_j x_j} \quad (5)$$

The G_i* model returns Z Scores and p-Values, which indicate whether to reject or not reject the null hypothesis on a unit by unit basis. A high positive Z-Score and significant p-value shows that there is a spatial clustering of high values (hot spot), while a low negative Z-score value with a significant p-value means that there is a spatial clustering of low values (cold spot). The intensity of clustering is measured by the size of the Z-Score value. A higher positive or lower negative Z-Score value means a more intense level of clustering. When the Z-Score value approximates zero (0), there is no apparent spatial clustering of values involved.

RESULTS

Road traffic crashes (RTC) and fatalities (RTF)

The total number of RTC from 2005 – 2018 was 133,412. That is an average of 9,530 crashes per year. Lagos and the Federal Capital Territory, Abuja posted the largest number of RTC in Nigeria, within the study period. Abuja had the worst case of RTC, with a total of 12,503. Lagos trailed second with 10,128 cases. States with large numbers of RTC (at least 5,000 or more each), in descending order are Kaduna (8,322) Ogun (6,671), Nasarawa (6,654), Ondo (5,733), Kano (5,459) and Niger (5,256). The states that registered the least number of RTC (less than 2,000 each), in descending order were Kebbi (1,824), Ekiti, Cross River, Rivers, Taraba, Bayelsa, Sokoto, Yobe, Abia and Borno (1,296) (Figure 2).

The total number of fatalities recorded within this 14 year period was 124,599; a mean rate of 8900 deaths every year. Kaduna State (9,840) and the FCT Abuja (9,070) had the largest numbers of RTF. Other states with more than 5000 deaths in the study period were Kano (6,320), Ogun (6,109), Nasarawa (6,058), Lagos (5,270), Kogi (5,211), Niger (5,207) and Oyo (5,032). The states that recorded less than 2000 deaths, in descending order of magnitude, were Adamawa (1,989), Kebbi, Ebonyi, Sokoto, Cross River, Abia, Taraba, Rivers, Ekiti, Akwa Ibom, Bayelsa (938) and Borno (911) (Figure 3).

It is noted that Kogi and Oyo states were not among the states considered as having high RTC (those with 5,000 or more) but they recorded more than 5,000 deaths within the same period. Lagos state had the second highest number of RTC but came a distant seventh in number of RTF. This demonstrates that the number of crashes alone does not tell the entire story. The rates of deaths per crashes is important to determine the risk of fatality and detect any patterns that may underlie the crash data in this regard.

Figure 5 shows the distribution of fatalities per crash for the states. The data shows that Yobe state, which neither had high RTC nor RTF had the highest rate of fatalities per crash. It recorded at least 1.48 deaths for every crash that was recorded. Other states with high rates of fatalities include Oyo (1.3), Katsina (1.3), Bauchi (1.22) and Osun (1.2). The implication of these statistics is that at least one person is likely to die in a crash in these states. Of the sixteen states that recorded at least one fatality per crash, 12 of them are in the northern part of Nigeria. Interestingly, Lagos state had the least rate and therefore risk of fatality (0.52) per crash. Others are Akwa Ibom (0.53) and Adamawa (0.55) states.

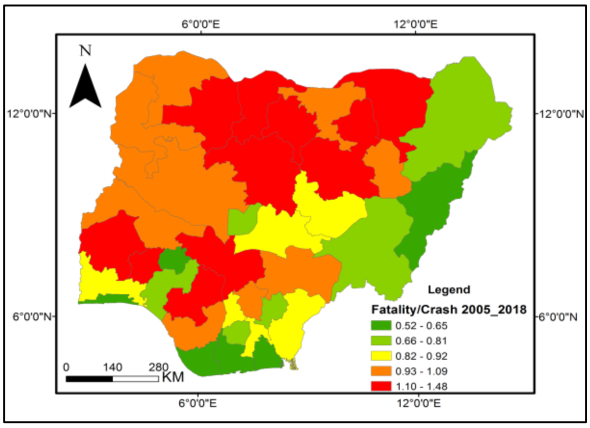


Figure 5: Fatality per Crash 2005-2018

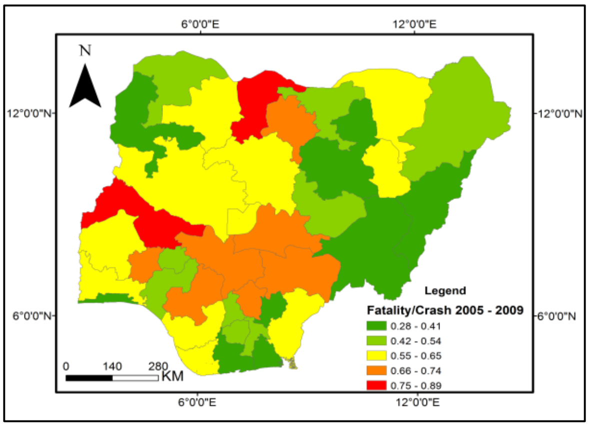


Figure 6: Fatality per Crash 2005-2009

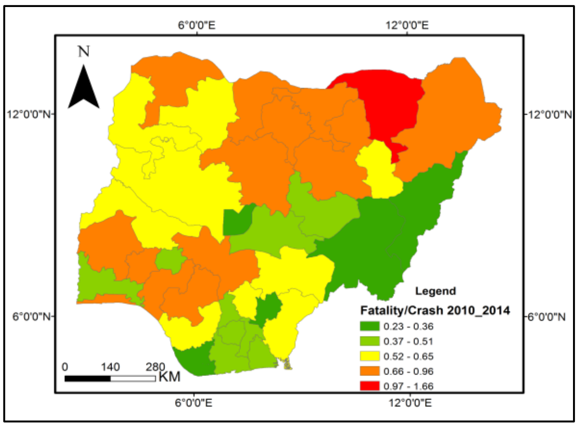


Figure 7: Fatality per Crash 2010-2014

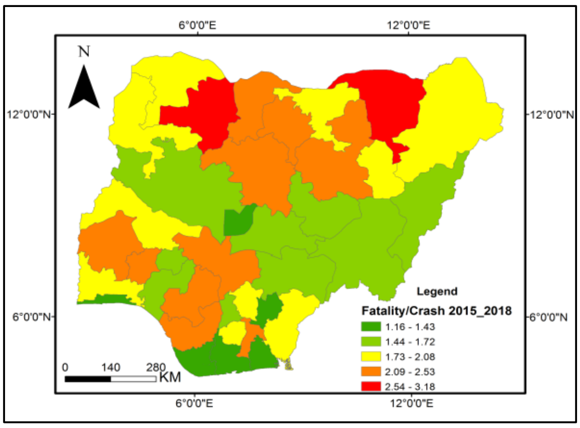


Figure 8: Fatality per Crash 2015-2018

The distribution of RTF rates shows a steady increase through the years. Between 2005 and 2018, there was an average of 0.95 fatalities per crash. In essence there was approximately one death for every crash. This is a dismal statistics for a country. Lagos (0.52) and Yobe (1.48) had the lowest and highest fatality rates. Between 2005 and 2009, there were 0.57 fatalities per crash with Lagos (0.28) and Kwara (0.89) recording the lowest and highest rates. On average the fatality rate increased to 0.62 fatalities per crash between 2010 and 2014. Bayelsa (0.23) and Yobe (1.66) had the lowest and highest rates. The 2015 - 2018 distribution had a sharp increase to 1.91 fatality per crash with Bayelsa (1.16) and Yobe (3.18) being the lowest and highest rates once again. These distributions, however, do not identify areas and levels of clustering of road traffic fatality rates. These are determined using spatial autocorrelation statistics.

Spatial clustering of rates of RTF (global)

Table 1 presents the results of Moran's I global statistics for rates of RTF.

Table 1: Moran's I Results

Time Period	Moran's I	Z Scores	P-Value	Remarks
2005 - 2009	0.187249	2.175218	0.029576	Clustered
2010 - 2014	0.211777	2.677416	0.007419	Clustered
2015 - 2018	-0.017553	0.104756	0.916569	Random
2005 - 2018	0.214571	2.44188	0.014611	Clustered

The global Moran's I results show that distributions of rates of RTF between 2005 and 2009, 2010 and 2014, and 2005 and 2018 were clustered. The period between 2015 and 2018, however, shows that any cluster of rate of RTF in the distribution was by chance.

The Getis-Ord General G statistics results are similar to the Moran's I except for the period between 2010 and 2014, which also indicated randomness along with rates of RTF distribution of 2015 – 2018. In these two time periods, rates of RTF did not exhibit spatial dependence. Table 2 presents the results of the General G statistics.

Table 2: Getis-Ord General G Results

Time Period	G Values	Z Scores	P-Value	Remarks
2005 - 2009	0.137534	2.039123	0.041438	Clustered
2010 - 2014	0.13303	0.5682	0.569899	Random
2015 - 2018	0.133278	1.087591	0.276776	Random
2005 - 2018	0.1391	2.405846	0.016135	Clustered

There are two immediate implications of these results. First, attention needs to be paid to the distributions found to be clustered. There is need for a closer scrutiny and deeper investigation of these distributions because they have the promise of interesting findings. Secondly, distributions with a global randomness do not necessarily translate to an assumption that they would contain no local clusters. It merely indicates that the entire distribution does not conform to a clustered pattern.

Spatial clustering of rates of RTF (local)

The local indicators of spatial autocorrelation (LISA) test and the Getis-Ord Gi* tests are therefore computed to detect where clusters exist in the distributions and whether the random distributions may have any pockets of clustered incidents. Table 3 shows the results of the Anselin's LISA.

Table 3: Anselin's LISA Results

Time Period	State	LMiIndex	LMiZScore	LMiPValue*	Remarks
2005 - 2009	Kwara	6.305521	3.123235	0.001789	High-High
	Kogi	7.057187	2.73135	0.006308	High-High
2010 - 2014	Yobe	7.85904	4.631316	0.000004	High-High
	Jigawa	4.888417	2.905139	0.003671	High-High
2015 - 2018	Delta	-5.27154	-2.513458	0.011955	High-Low
2005 - 2018	Katsina	4.773803	2.597763	0.009383	High-High
	Kano	3.650183	2.000237	0.045475	High-High
	Bauchi	4.540158	1.995163	0.046015	High-High
	Rivers	5.176451	2.39289	0.016716	Low-Low

For the period between 2005 and 2018, Katsina, Kano, Bauchi and Rivers states exhibited significant positive spatial autocorrelation. States with RTF rates of similar values are clustered together. The three northern states of Katsina, Kano

and Bauchi formed a cluster of high RTF rates. Rivers State has low rate of RTF and is surrounded by neighbouring states with low values as well. Figure 5 shows that Rivers state is surrounded by neighbours (Edo, Bayelsa, Akwa Ibom, Abia, Imo, Anambra and Delta), which had low values of RTF rates, except for Delta.
Figures 9 and 10 show the LISA results of RTF distribution for the 2005 – 2018 and 2005 – 2009 periods.

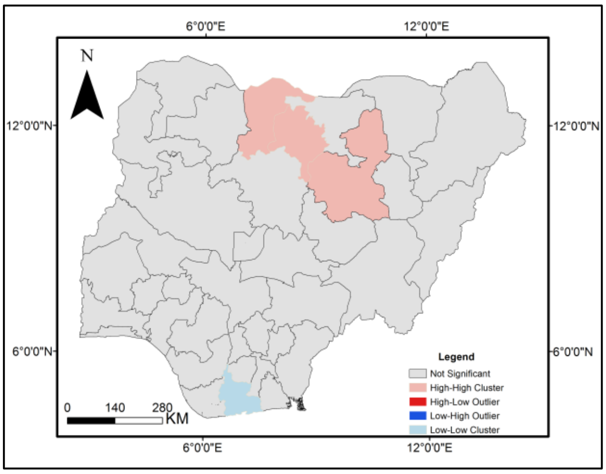


Figure 9: LISA: RTF, 2005 – 2018

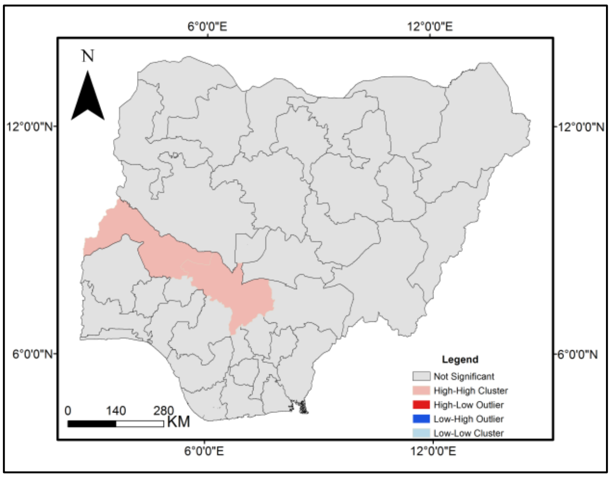


Figure 10: LISA: RTF, 2005 - 2009

Between 2005 and 2009, Kwara and Kogi displayed a high-high cluster of RTF rates. Kwara states had one of the highest numbers of RTF rates. It is bordered by five states, two (Kogi and Osun) had high values and the remaining three (Oyo, Ekiti and Niger) had average rates. Kogi also had high rates of RTF and is surrounded by ten states, two (Ondo and Ekiti) registered low rates, two others (FCT and Niger) had average rates, one (Kwara) registered very high rates and the remaining five had similar high rates to Kogi.
Between 2010 and 2014, Jigawa and Yobe were the states with a high-high cluster, while only Delta state showed significantly high value of RTF in the 2015 – 2018 distribution. Since it is surrounded by neighbouring states with low RTF values consequently, it exhibits negative spatial autocorrelation (Figures 11 and 12).

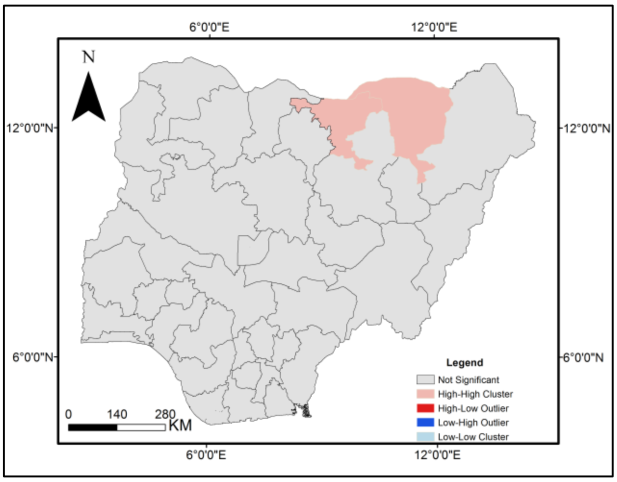


Figure 11: LISA: RTF, 2010 – 2014

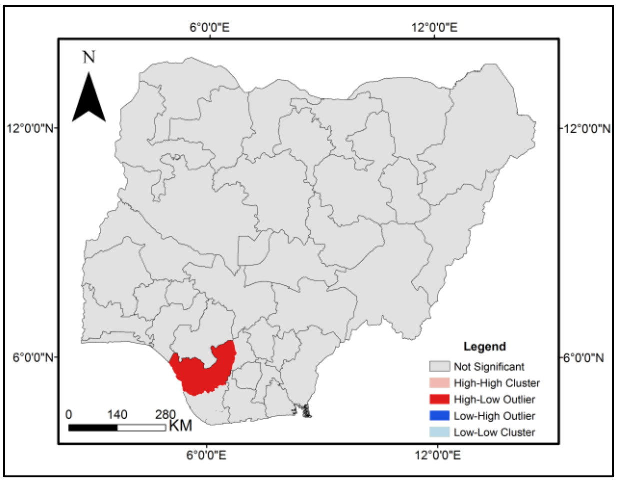


Figure 12: LISA: RTF, 2015 - 2018

Except for Delta state, which shows a high cluster of RTF rate in the 2015-2018 distribution, all the states with high RTF rate clusters are from the North of Nigeria (Katsina, Kano, Yobe, Jigawa and Bauchi). Interestingly, no single state is consistent through the study periods. The Delta state scenario is the only negative spatial autocorrelation in the distributions, while Rivers state is the only state with low values that is surrounded by neighbours with low values.
The Getis-Ord Gi* determines local areas of spatial clustering. It measures whether an area unit of analysis has values that are higher (hot spot) or lower (cold spot) than expected.
Table 4 shows that all the hot spots of RTF rates between 2005 and 2018 are northern states. Except for Kebbi state, which is only significant at 0.10, the remaining four states have significant clusters of RTF rates. Jigawa state is significant at 0.01 level.
Table 4 presents the results of the Gi* analysis.

Table 4: Gi* Results

Time Period	State	GiZScore	GiPValue	Remarks
2005 - 2009	Kwara	2.248102	0.02457*	Hot Spot
	Kogi	2.430587	0.012753*	Hot Spot
	Oyo	2.21708	0.026618*	Hot Spot
	Ekiti	2.099474	0.035775*	Hot Spot
	Osun	1.678811	0.093189	Hot Spot
	Adamawa	-1.80005	0.071853	Cold Spot
	Gombe	-1.1267	0.054017	Cold Spot
2010 - 2014	Kano	1.83615	0.066336	Hot Spot
	Borno	1.721256	0.085204	Hot Spot
	Jigawa	3.593644	0.000326*	Hot Spot
	Yobe	2.894426	0.003799*	Hot Spot
	Bauchi	1.984624	0.047186*	Hot Spot
	Rivers	-2.22643	0.025986*	Cold Spot
	Imo	-1.64928	0.09909	Cold Spot
	Abia	-1.87604	0.06065	Cold Spot
2015 - 2018	Katsina	2.116781	0.034278*	Hot Spot
	Jigawa	2.495323	0.012567*	Hot Spot
	Bauchi	1.674032	0.094125	Hot Spot
2005 - 2018	Jigawa	2.984941	0.002836*	Hot Spot
	Kano	2.376441	0.017481*	Hot Spot
	Katsina	2.254741	0.02415*	Hot Spot
	Bauchi	2.029068	0.042451*	Hot Spot
	Kebbi	1.873609	0.060984	Hot Spot
	Rivers	-2.26573	0.023468*	Cold Spot
	Abia	-1.84515	0.065016	Cold Spot
	Akwa Ibom	-1.8372	0.066181	Cold Spot

*Values significant at 0.05 level. The remaining are significant only at 0.10 level.

Inversely, three states in the South exhibited lower than expected rates of RTF and therefore showed up as cold spots. Rivers is significant at 0.05 while Abia and Akwa Ibom are only significant at 0.10. Figures 13 and 14 display the results for 2005 – 2018 and 2005 – 2009 distributions.

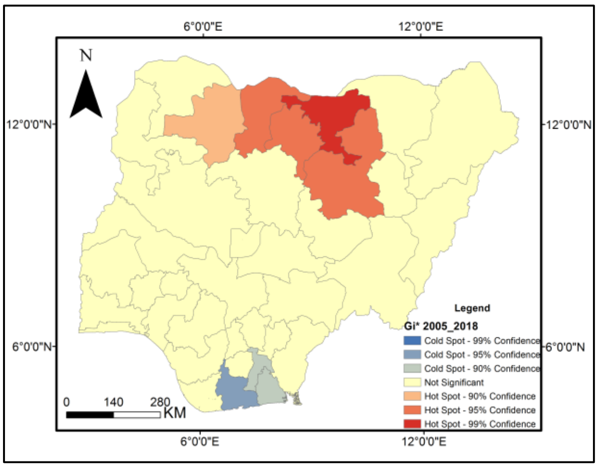


Figure 13: Gi*: RTF, 2005 – 2018

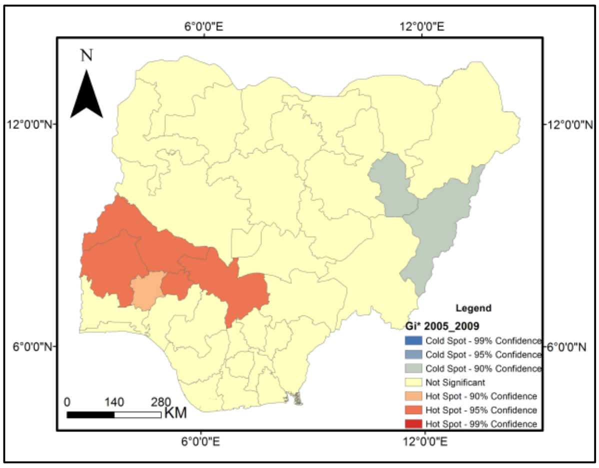


Figure 14: Gi*: RTF, 2005 - 2009

Between 2005 and 2009, two states in north-central and three in the southwest showed high clusters of RTF rates. Two states in the northeast, however, were cold spots. In the overall model (2005 – 2018), none of the states showing high rates of RTF clusters at the decomposed 2005 – 2009 distribution, is significant. It is different at the 2010 and 2014, and 2015 – 2018 distributions. Many of the states that show significant clusters at the 2005 – 2018 are also prominent clusters at the decomposed levels (Figures 15 and 16).

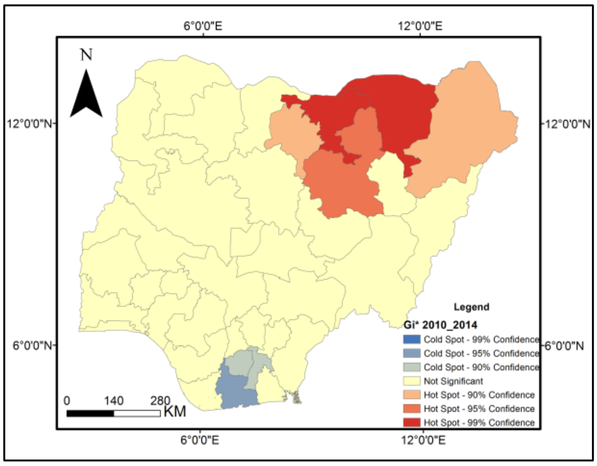


Figure 15: Gi*, 2010 – 2014

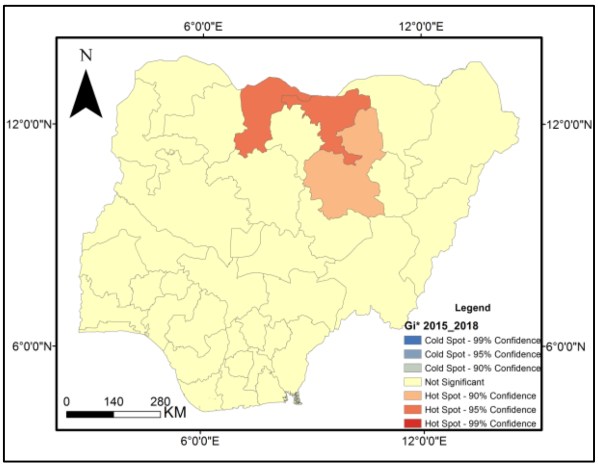


Figure 16: Gi*, 2015 - 2018

The hot spot and cold spot distributions for 2010 and 2014 are largely identical with that of the 2005 – 2018: Jigawa, Bauchi and Kano are also hot spots while Rivers and Abia are cold spots. While the 2005 – 2018 distribution had the hot spots leaning northwest, the 2010 – 2014 distribution leaned northeast, with the addition of Yobe and Borno among the RTF hot spot states. Kano and Borno are significant hot spots only at 0.10 level. Instead of Akwa Ibom, Imo joined the cold spots in the south, but along with Abia, is only significant at the 0.10 level.

There appears to be a dichotomy between the northern and southern states in regards to rates of RTF. Most of the hot spots are found in the north, while most of the cold spots are in the south. The states of Katsina, Jigawa and Bauchi appear to be at the heart of the hot spots.

According to Osayomi and Areola (2015), spatial autocorrelation of crash data between 2002 and 2007 revealed a southwest belt of high road traffic crashes, injuries and deaths. The analysis was based on crash, injury and death rates computed per 100,000 of the population. Ukoji (2016) used a similar rate (death per 100,000 persons) to examine road traffic fatalities in Nigeria between 2006 and 2014. The data used, however, was from a website, Nigeria Watch, based on reported crash data sourced from news media. The author acknowledged the inadequacy in this source of data. The analysis, however, showed that southern Nigeria had more fatalities and rates of deaths than northern states.

Though this study found differently, it is important to point out that the rate of fatality measured in this study was fatality per crash not fatality per 100,000 persons as was the case with the other studies, which makes it difficult to compare the results directly. The rate of fatality per crash provides an insight into the likelihood of a fatality occurring in a crash incident, in which the northern states showed up much worse than the southern states. Many factors may be responsible for this established pattern. The northern states have relatively low levels of population densities, car ownership and road infrastructural density. This is in addition to the fact that Nigerian roads are poorly constructed and maintained. Topographically, the roads in Northern Nigeria are relatively flat because of the natural terrain of many northern states. In regards to size, the northern states are disproportionately larger than the southern states, with dispersed settlements, which require long distance travel between towns. These characteristics favour high speed of driving.

In many parts of Africa, over-speeding and reckless driving behaviours are the major causes of RTC (Boateng, 2021). The Nigerian National Bureau of Statistics (NBS) (2020) reported that speed violation was responsible for 48% of all crashes in the second quarter of 2020 and is the major cause of RTC in Nigeria. Yero, Ahmed and Hainin (2015) stated that speed violations by drivers, coupled with bad road conditions was responsible for the high rates of crashes and fatalities along the Maiduguri-Potiskum highway section of the North-East Highway. Yunus and Abdulkarim (2021) asserted that drivers' violations of speed limits was the major cause of road traffic crashes and fatalities in Kano state. Yahaya, Yusuf, Musa, Ma'aji, Bambale, Oscar, Bawa and Onuawaka (2021) found similarly in Kaduna state. This scenario is common in almost all parts of Nigeria. In the northern states, however, there appears to be an added consequence. With relatively fewer motor vehicles on roadways that are flat, most drivers are tempted to drive at high speed in road unworthy vehicles. A crash in such conditions would mostly likely result into a fatality.

Richards (2010) concluded that the risk of fatality increases with higher driving speeds. According to the Institute for Road Safety Research (2012), the higher the driven speeds of vehicles the higher and greater the crash rate and injuries severity. The US National Highway Transportation Safety Administration (NHTSA) (2021) stated that (over) speeding remains the number one factor in more than 25% of fatal crashes every year in the USand is recognized as the leading cause of crashes and deaths.

According to Ackaah and Salifu (2011) and Hu, Li, Liu and Adanu (2021) roads with grades or curves were associated with less frequent crashes compared to straight and flat roads, especially along rural highways. Ackaah and Salifu (2011) further indicated that about 70% of road traffic fatalities in Ghana were accounted for by rural crashes.

Many of the roads in northern Nigeria are relatively flat and straight because of the terrain, rural and with low traffic density, which allow for high driving speeds. With a large number of vehicles not being road worthy and poor road surfaces and conditions, high driving speeds attract crashes and high degrees of fatalities.

CONCLUSION

First, the study analyzed the spatial autocorrelation of road traffic fatalities in Nigeria using the rate of fatalities per crash and demonstrated that it is an effective rate to measure and investigate road traffic fatalities in Nigeria. Second the study revealed that contrary to many earlier studies and expectations, northern Nigeria appears to be a core hot spot of concern for road traffic crash fatality. The study found that there appears to be a higher likelihood of death occurring in a road traffic crash in the northern states of Nigeria than in the south. There is, therefore, an urgent need to examine these hot spots of crash fatalities. Third, the study raised questions as to the cause of these hot spots region in the north and proposed a hypothesis that is centred on road geometry and traffic and driving behavior rather than the zonal characteristics of the region, including population and socio-economic attributes of the hot spot region, which are the more popular variables generally considered. However, the study also noted that a major problem, which continuously plagues aggregate data analysis is the aggregation bins problem. There is always the potential to obtain different results from the same data when different spatial and/or temporal aggregation levels are used. These are commonly referred to as the modifiable area unit problem (MAUP) and the modifiable temporal unit problem (MTUP). It is therefore necessary to analyze aggregate data at different spatial and temporal scales and attempt to identify any trends or patterns in them that would be useful to selecting an optimum aggregation band. In the Nigerian context, with the level of technology available, it is high time that crash incidents data be collected and made available to researchers at precise location specificity using GPS technology. This would guarantee a more detailed level of data analysis.

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