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Original Article

A spatiotemporal analysis of crimes reported in the North Shewa Zone of Amhara region, Ethiopia

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Abstract

Crime is a societal problem that has an impact on the quality of life and economic prosperity of a society. So, crime data analysis is used to understand more about how and why crime happens, as well as the policy measures to reduce its rate. Thus, this study focused on a spatiotemporal analysis of crimes perpetrated in North Shewa Zone between September 2018 and August 2020. The crime data were collected using files from the North Shewa Zone Police office for each district during the years in question to evaluate it. The spatial shapefiles were then geocoded and non-spatially connected using Google Maps to produce the geographic coordinates latitude and longitude. Cluster sampling technique was used to determine the number of districts included in the study. The Moran's I and Gertis-Ord methods were used. The Moran's I statistics for crimes from September 2018 to August 2019 and September 2019 to August 2020 were 0.079 (Z-score = 3.685; p = 0.000228), and 0.0482 (Z-score = 2.567; p = 0.010248), respectively. In both years, there was a clustered distribution of crimes, or there was spatial dependence among places. Similarly, Getis-Ord Gi* indicated that in several of the analyzed districts, the majority of the study wards had statistically significant crime hotspots.

Keywords: crime, cluster sampling, GIS, hotspots, spatial autocorrelation

1. Introduction

Crime is a social problem that affects the quality of life and economic development of any society (Bogomolov *et al.*, 2015), so it is necessary to determine the locations of different crime types in space and time (Mafumbabete, Chivhenge, Museva, Zingi, & Ndongwe, 2019). Crimes can be divided into several types, such as crime of property (theft, burglary and robbery), and crime of aggression (murder, assault and rape), etc.

In 2000, in the official report of the International Criminal Police Organization (INTERPOL), Ethiopia's crime rate was quite low compared with other developed countries (Blackburn & Matthews, 2011). However, this could be attributed to a lack of official reporting when criminal acts were taking place, and a traditional criminal record system. Thus, there is a need for accurately identified crimes and clearly visualized crime maps, which can significantly benefit police practices by aiding threat visualization, police resource allocation, and crime prediction (Lin, Chu, Wu, Chang, & Chen, 2011). In this regard, studying crime data is used to understand when and where crimes occur, to provide information for policy responses that can reduce future crimes and their negative consequences.

Criminal activities are often unevenly distributed across a geographic area (Brantingham, 2016), and rather often concentrated in specific communities or settings (Statistics Canada, 2015). Several techniques and models have been developed to meet the need for predictive policing with available data. One of the most popular methods is the spatial hotspot model, where the hotspots are high-risk areas in which crimes are concentrated (Bowers, Johnson, & Pease, 2004). However, this only shows the current crime patterns without providing understanding of the relationship between crime and the environment over time: as the local environment changes, the hotspot model cannot show changes in crime patterns (Wang & Brown, 2012). Therefore, analyzing crime patterns and predicting crime trends is essential to reduce the rate of re-victimization; and this needs to be done by examining local variations in crime variability over space and time (Hu, Zhu, Duan, & Guo, 2018).

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Although many interdisciplinary criminal activities have happened in different parts of Ethiopia over the years, this study focuses specifically on crimes recorded in the North Shewa Zone from September 2018 to August 2020. This is due to a very nasty event that followed the unstable political transition of Ethiopia. This study was also initiated as many studies have merely considered the spatial element of crimes and not jointly examined spatial and temporal aspects of crime. But a combined analysis of spatial and temporal aspects of crimes is very important instead of only studying space or time independently. Therefore, this study primarily focused on a spatiotemporal analysis of crime, especially on identifying hotspots in the North Shewa Zone, Amhara regional state, Ethiopia, from September 2018 to August 2020.

2. Methods and Materials

2.1 Study area and design

The study area is the North Shewa Zone. It is one of the 10 primary zones in the Amhara regional state, Ethiopia, with its own geographic coordinates during the 2007 census. Based on the 2007 Ethiopian Census, the estimated/projected total population of in the zone is 2,131,857, an increase of 17.72% from the 1994 Census, of which 1,075,206 are males and 1,056,651 are females (Ethiopia Central Statistical Agency [CSA], 2013). The North Shewa Zone has a population density of 115.30 and covers an area of 15,936.13 square kilometers, with 214,227 or 11.66% being city dwellers. There are 429,423 households in the area, averaging 4.28 per household and 413, 235 residential units.

2.2 Data and sampling

In the study, data by crime type were collected using file analysis for each district recorded in the North Shewa Zone Police office in the aforementioned years. However, the location of the crime was not captured using GPS at each X, Y coordinate, but instead geocodes of the data were used to generate geographic coordinate values (latitude, longitude) using Google Maps, and non-spatially joining with the spatial shapefile was done. Cluster sampling was applied to select districts to be included in the study. All twenty-two districts in the zone were divided into five non-overlapping clusters, then second, fourth and fifth clusters were selected using simple random sampling (SRS) technique, those containing all entire districts. Finally, a total of twelve districts were included in the study.

2.3 Data analysis

A number of descriptive and exploratory data analysis approaches were used in the study. To see if the crimes were spatially related, point map techniques for crime pattern mapping, spatial autocorrelation, and specifically Moran's I statistics were used (Anselin, 1995).

The spatial autocorrelation analysis particularly was used to test whether the crimes observed at one location were independent of the crimes at adjacent locations. If there is a dependency, the crimes are said to have spatial auto correlation. This spatial autocorrelation can be either positive or negative. When positive, crimes appear to have clustered distribution, whereas with negative spatial autocorrelation, different values appear closely related. For simplicity, the null and alternative hypotheses could be stated as follows, respectively.

H0: Crimes are spatially distributed in a random process (i.e. spatially independent)

H1: Crimes are spatially clustered, i.e., they are spatially dependent

Gertis Ord Gi* hotspot analysis was also utilized to identify areas with high crime rates. An examination of the temporal and geographical crime patterns of property and violent crimes was done to analyze the changes in crime patterns through time and geography. Different software programs were used for data administration and analysis, including Geographic Information System (GIS)-ArcMap version 10.6, STATA version 14.2, and SPSS version 25.

3. Results and Discussion

3.1 Descriptive summary

Burglary, robbery, murder, rape and theft, all of which were categorized as physical and violent crimes, are summarized in each research region for each study year in Tables 1a and 1b. It is seen that the most common crime type perpetrated throughout the two study years was stealing, followed by assault and robbery. Burglary, along with murder and rape, are among the least crime categories committed throughout each study year, and rape is substantially lower than the other types (Tables 1a and 1b). When comparing individual investigative districts based on crime rates, Antsokia, Menz Gera, Mida Woremo, Efratana Gedim, Minjar Shekora, and Hagere Mriam had the highest crime rates. In contrast, Kewet and Merhabete had the lowest rates between September 2018 and August 2019 (Table 1a).

Similarly, Antsokia, Minjar Shekora, and Gishe Rabel had the highest crime rates from September 2019 to August 2020, whereas Assagirt and Berehet districs had the lowest rates (Table 1b). In general, crime rates from September 2018 to August 2019 were slightly higher than rates those from September 2019 to August 2020. Furthermore, in both accounted study years, Antsokia district had higher crime rates than the other districts.

3.2 Crime patterns/distribution

Property crimes occurred in significant concentratio ns in study districts such as Hagere Mariam, Ensaro, Gishe Rabel, and Antsokia between September 2018 and August 2019 (Figure 2a), while violent crime rates from September 2018 to August 2019 were concentrated in Northern Kewet, Antsokia, and Gishe Rabel (Figure 2b).

3.3 Spatial autocorrelation

The Moran's I score data are found in the upper left corner of two consecutive figures and are used to see if there is any crime autocorrelation between them (Figures 3a and 3b). The scores from September 2018 to August 2019 is 0.079 (z-score = 3.685; p = 0.000228), and from September 2019 to August 2020 is 0.0482 (z-score = 2.567; 0.010248) indicate

Table 1a. Numbers of crimes of property (burglary, robbery, theft) and crimes of violence (murder, assault, rapes) committed in the North Shewa Zone in some selected districts (Sep, 2018 to Aug, 2019).

Year	District	Crime Types: Count (%)						
		Assault	Burglary	Murder	Rape	Robbery	Theft	Total
Sep, 2018 to Aug, 2019	Antsokia	19(24.36)	8(10.26)	10(12.82)	4(5.13)	6(7.69)	31(39.74)	78(100)
	Assagert	7(17.50)	3(7.50)	5(12.50)	2(5.00)	5(12.50)	18(45.00)	40(100)
	Berehet	9(23.08)	2(5.13)	6(15.38)	2(5.13)	3(7.69)	17(43.59)	39(100)
	Efrata Gdim	14(22.95)	6(9.84)	11(18.03)	8(13.11)	6(9.84)	16(26.23)	61(100)
	Ensaro	9(20.00)	3(6.67)	6(13.33)	2(4.44)	6(13.33)	19(42.22)	45(100)
	Gishe Rabel	15(25.86)	4(6.90)	6(10.34)	4(6.90)	5(8.62)	24(41.38)	58(100)
	H/Mariam	26(44.07)	3(5.08)	6(10.17)	2(3.39)	5(8.47)	17(28.81)	59(100)
	Kewet	8(18.60)	4(9.30)	6(13.95)	3(6.98)	5(11.63)	17(39.53)	43(100)
	Menz gera	19(24.68)	8(10.39)	9(11.69)	4(5.19)	11(14.29)	26(33.77)	77(100)
	Merabete	9(20.45)	4(9.09)	5(11.36)	6(13.64)	4(9.09)	16(36.36)	44(100)
	Mida woremo	25(37.88)	4(6.06)	10(15.15)	6(9.09)	4(6.06)	17(25.76)	66(100)
	Minjar Shenkora	17(27.87)	3(4.92)	6(9.84)	3(4.92)	8(13.11)	24(39.34)	61(100)

Table 1b. Numbers of crimes of property (burglary, robbery, theft) and crimes of violence (murder, assault, rapes) committed in the North Shewa Zone in some selected districts (Sep, 2019 to Aug, 2020).

Year	District	Crime Types: Count (%)						
		Assault	Burglary	Murder	Rape	Robbery	Theft	Total
Sep, 2018 to Aug, 2019	Antsokia	29(31.52)	6(6.52)	9(9.78)	5(5.43)	7(7.61)	36(39.13)	92(100)
	Assagert	10(27.03)	4(10.81)	3(8.11)	0(0.00)	5(13.51)	15(40.54)	37(100)
	Berehet	10(25.00)	3(7.50)	2(5.00)	3(7.50)	3(7.50)	19(47.50)	40(100)
	Efrata Gdim	11(19.30)	9(15.79)	9(15.79)	8(14.04)	7(12.28)	13(22.81)	57(100)
	Ensaro	12(24.00)	6(12.00)	9(18.00)	3(6.00)	7(14.00)	13(26.00)	50(100)
	Gishe Rabel	19(29.69)	3(4.69)	7(10.94)	5(7.81)	4(6.25)	26(40.63)	64(100)
	H/Mariam	17(36.17)	3(6.38)	5(10.64)	1(2.13)	3(6.38)	18(38.30)	47(100)
	Kewet	12(23.08)	5(9.62)	9(17.31)	3(5.77)	6(11.54)	17(32.69)	52(100)
	Menz gera	14(26.92)	5(9.62)	7(13.46)	3(5.77)	6(11.54)	17(32.69)	52(100)
	Merabete	12(25.00)	4(8.33)	6(12.50)	4(8.33)	5(10.42)	17(35.42)	48(100)
	Mida woremo	17(34.00)	3(6.00)	7(14.00)	3(6.00)	5(10.00)	15(30.00)	50(100)
	Minjar Shenkora	19(28.36)	4(5.97)	8(11.94)	2(2.99)	6(8.96)	28(41.79)	67(100)

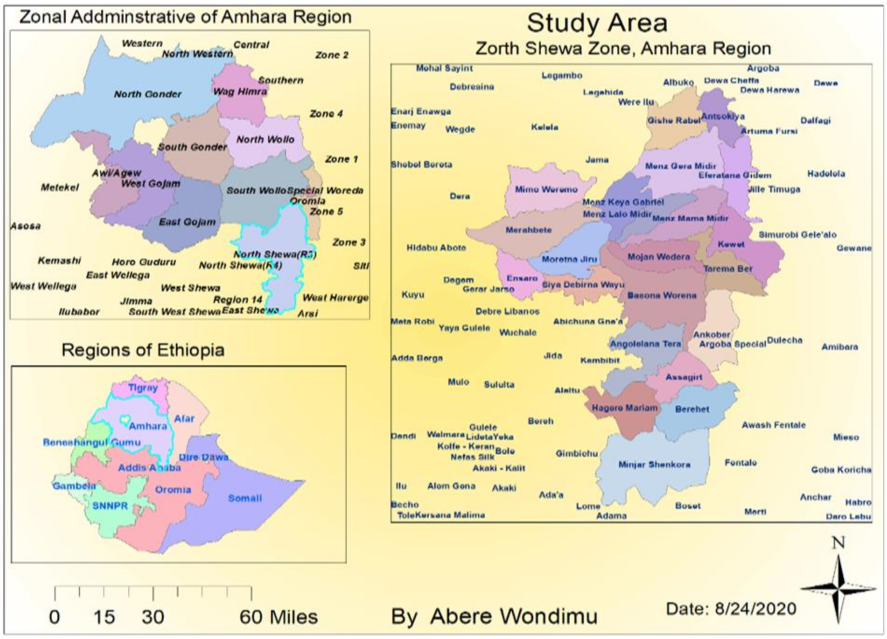
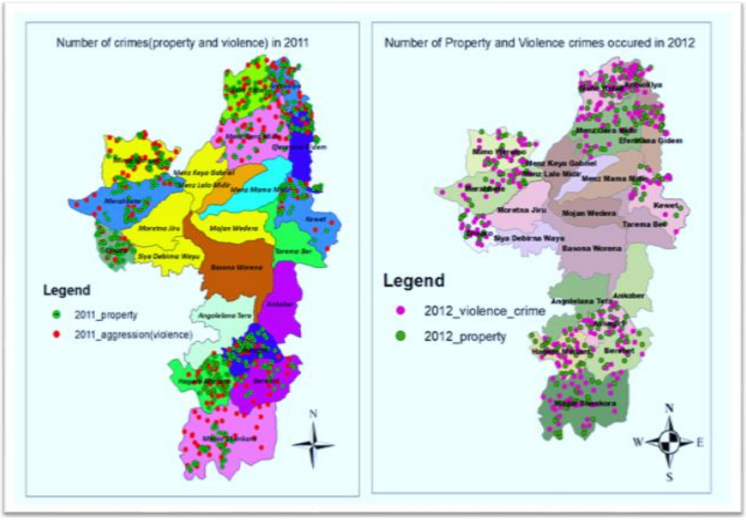


Figure 1. Map of North Shewa Zone, the current study area (Shapefile source: 2007 Census)



a. spatial pattern of crime in Sep, 2018 to Aug, 2019(2011 E.C)

b. spatial pattern of crime from Sep, 2019 to Aug, 2020 (2012 E.C)

Figure 2. Spatial and temporal distribution of crimes in North Shewa Zone for some selected districts 2018 to 2020 (2011 to 2012 E.C.)

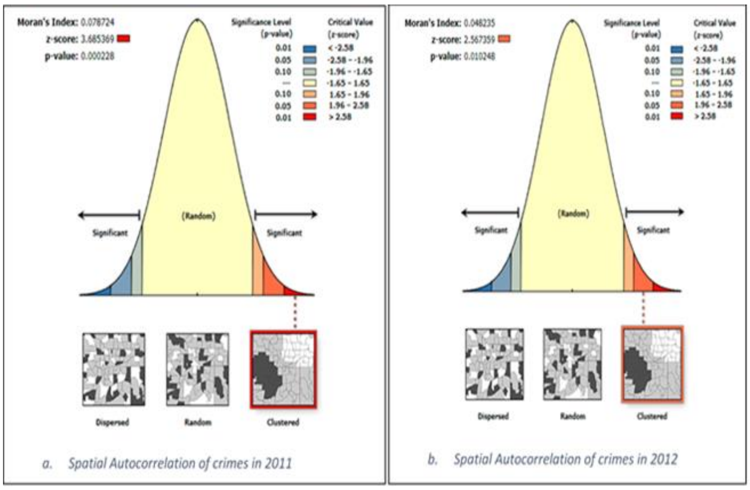


Figure 3. Tests of spatial autocorrelations of crimes among areas in some selected districts in the North Shewa Zone from Sep 2018 to Aug 2020 (2011 to 2012 E.C.)

that crimes in the North Shewa Zone were spatially dependent, or they had significant spatial autocorrelations with crimes committed throughout the study districts.

The z-scores from September 2018 to August 2019 and from September 2019 to August 2020 were 3.685 and 2.567, respectively. This suggests that the clustering trend could be due to chance with a probability of less than 1%. Colors other than red (such as blue) are used in Figure 3. In short, we found statistically significant p-values and positive z-scores. In this case, we can conclude that the spatial distribution of high and/or low crimes is more spatially clustered than would be expected if the underlying spatial processes were random.

3.4 Hot spots analysis of crimes

Figure 4 shows that the G* statistics ranged between 0.577 and 1.766 from September 2018 to August 2019, and between 0.245 and 1.44 from September 2019 to August 2020, indicating significant clustering of criminal offenses with a 95% confidence level. The z-scores and p-values are also used to determine whether the data are spatially clustered. Table 2 shows that some of the research areas (features) show a geographic accumulation of high crime rates (z= 5.423; p = 0.000011 and z=9.572; p = 0.000) for consecutive years, implying that some of the study areas (features) show a spatial accumulation of high crime rates.

In particular, wards (kebeles) within corresponding districts such as Girara Amba, Del and Rabel in Gishe Rabel; Ateko, wajit, Mekoy and Gishoge in Antsokia; Tere, Wekfele, Yelen in Kewet; Tegora, Monaze, Garda in Mida woremo; Lamgano, Lemi, Diramu in Merhabete; Arerti, Boloslase, Chole, Akele, Kormash in Minjar-Shenkora; Sechat, Akirmit, Yelet, Sekoru in Hagere Mariam; Wona, Tamo in Asagirt were identified as hotspot areas (Figure 5).

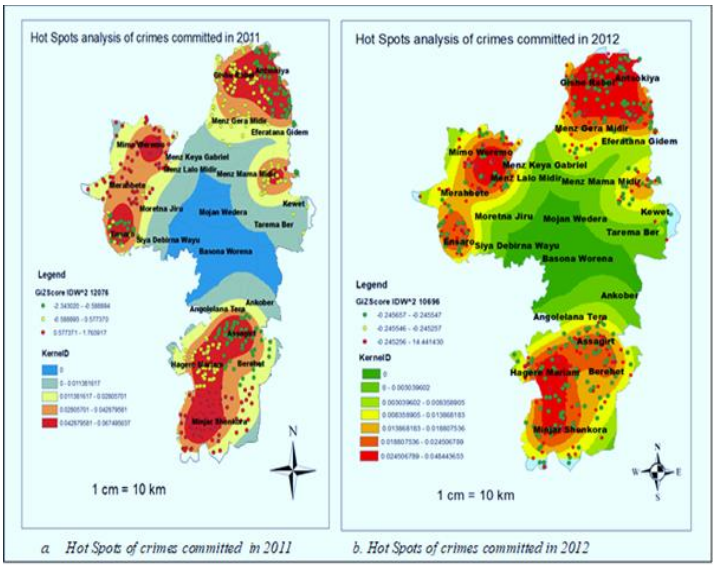


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Figure 4. Hotspot analysis of crimes to determine particular areas of densely concentrated events in the North Shewa Zone from Sep, 2018 to Aug, 2020 (2011 to 2012 E.C.)

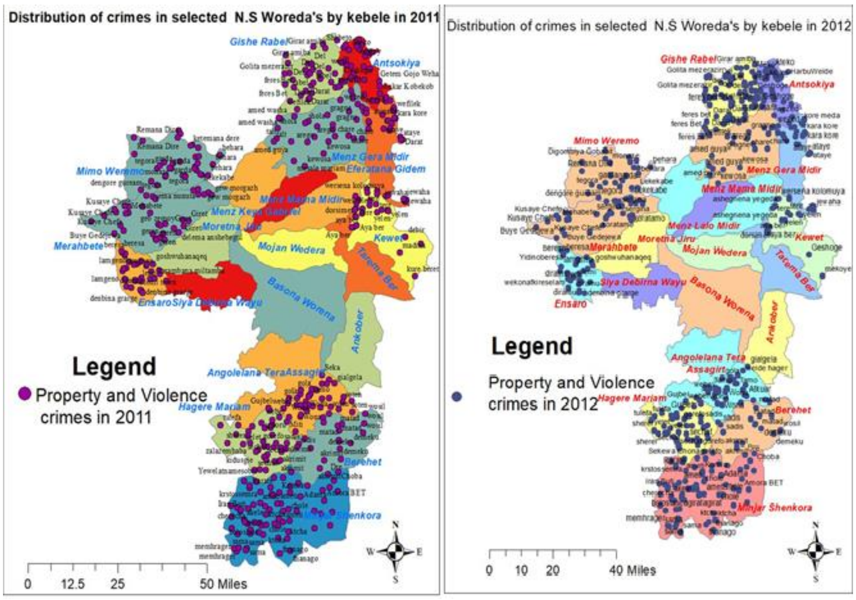

Figure 5. Distribution of crimes in the wards from Sep, 2018 to Aug, 2020 (2011 to 2012 E.C.)

Table 2. The overall z-score and p-value statistics of crime in Sep, 2018 to Aug, 2020

Sep, 2018 to Aug, 2019		Sep, 2019 to Aug, 2020	
z-score	5.423	z-score	9.572
p-value	0.000011	p-value	0.0000

4. Discussion

The main goal of this study was to undertake a spatiotemporal analysis of crimes recorded in selected districts in the North Shewa Zone from September 2018 to August 2020, with the goal of analyzing spatial autocorrelation and identifying crime hotspots.

The descriptive analyses revealed that theft, assault, and robbery were the most common crime types during the study's time period. Burglary was one of the lower ranking crimes during each study period, along with murder and rape, and rape was extremely infrequent compared to the other crimes. However, this contrasts a study conducted in Pakistan (Umair *et al.*, 2020), which found that robberies are the most common crime event. In general, crimes committed from September 2018 to August 2019 were greater in some ways than crimes committed from September 2019 to August 2020, when reporting errors as well as criminal incidence in time and space were taken into account.

According to the geographical distribution and crime cluster model, the statistics for Moran I value from September 2018 to August 2019 and September 2019 to August 2020 are 0.079 (Z-score = 3.685; p=0.000228) and 0.0482 (Z-score=2.567; p=0.010248), respectively, implying that the data were spatially clustered (dependent). This contradicts the findings of another study, which has shown that the geographical pattern of crime is irregular and that regional disparities are consistent. Here, the potential reasons why crimes were found to be spatially correlated (spatially dependent) between neighborhood localities could be guessed. That is, the zone bordered by other different regions and zones with different identities such as languages, races, ethnic groups, and territorial claims, has resulted in various conflicts and crimes.

Obviously, temporal variations of crimes generally follow patterns known from time series analysis, but the spatial patterns are irregular and vary unevenly across regions. However, consistent with (Aldor, Brown, Fox, & Stine, 2013), the present study suggests that different geographic regions have associated crime patterns. The results of this study are also consistent with the fact that hotspots and criminal groups were found to be scattered in a specific place (ward) (Mafumbabete *et al.*, 2019).

In particular, the neighborhoods of Girara Amba, Del and Rabel in Gishe Rabel; Ateko, wajit, Mekoy and Gishoge in Antsokia; Tere, Wekfele, Yelen in Kewet; Tegora, Monaze, Garda in Mida Woremo; Lambano, Lemi, Diramu in Merhabete; Arerti, Boloslase, Chole, Akele, Kormash and MinjarShenkora; Sechat, Akirmit, Yelet, Sekoru and Hagere Mariam; Wona, Tamo in Asagirt have been identified as sensitive areas (Figure 5). This can help the police and law enforcement agencies implement crime-fighting strategies in problem areas to reduce crime and protect lives and property (Khalid, Wang, Shakeel, & Nan, 2016).

The findings of the current study indicate that the distributions of major crimes in property crimes and violent crimes in the study periods were almost homogenous, and this is consistent with a prior study (Wang, Lee, & Williams, 2019). Overall, the findings revealed that the districts not included in the study could be considered neighborhood areas where crime activities are geographically associated.

5. Conclusions

The findings of this study revealed that there was a spatial autocorrelation between crime rates among study locations. The report also highlights crime hotspots in particular districts, such as Antsokia, which are clearly vulnerable to property crimes and/or violent criminal activity. As a result, specific measures in the identified hotspot districts are urgently needed to promote public safety by decreasing or preventing crime in these areas.

Hotspot analysis is a useful tool in this regard because it allows the police to identify locations with high crime rates and trends. However, anti-crime efforts are not primarily the responsibility of law enforcement agencies like the police. They should be a part of a community-wide effort to put anti-crime strategies in place in high-risk locations.

6. Words Interchangeably used in the Study

- Districts = Woredas (Ethiopian administration at fourth level)
- Wards = Kebeles (Ethiopian last/small administration or fifth level)
- Zone is the Ethiopian administration at third level next to Region.

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