Journal of Geomatics Vol. 14, No.1, April 2020

Mapping of crime incidences and hotspot analysis through incremental auto correlation – A case study of Shillong city, Meghalaya, India

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(Received: Feb 14, 2020; in final form: June 30, 2020)

Abstract: The mapping of crime incidents in the spatio-temporal domain is one of the vital components to take up more decisive steps to minimize crime incidents. Distribution of crime incidents is not accidental as they occur due to the various socio-economic as well as environmental conditions. It has been reported that crime rates are rising frighteningly in developing countries. In India, several studies on the analysis of crime patterns, trends, and the causes have been carried out with the inputs from geospatial technology. There is no detailed study on the analysis of crime hotspots using spatio-statistical techniques for the Shillong city of Meghalaya, India. The main objective of this work is to determine the pattern of crime hotspots during different time frames for the Shillong city using the incremental spatial autocorrelation method. Three years of crime incident data (2014-2016) comprising of more than 4515 incidents were analyzed and categorized mainly in 5 major types such as house trespassing, murder, crimes against women, theft, and cheating related charges. The intensity of the spatial clustering of the crime incidents were obtained effectively by the *z*-score measured by increasing the distance band or threshold distance, which helped to understand the spatial distribution of crime incidents with a higher degree of confidence level. It was observed that the hotspots were primarily confined to the central part of the city and some of the hotspots (average) were unevenly distributed over space irrespective of the size of the population density. The crime against women were reported mostly during the evening and the highest theft were reported after 2200 hrs during night. Other crime cases were not observed with any specific pattern concerning the time of occurrences.

Keywords: Spatial autocorrelation, spatial distribution, spatial clustering, hotspots

1. Introduction

The crime rates are increasing alarmingly in all the developing countries due to various reasons like poor social, political, economic, and environmental conditions. The distribution of the crime incidents is not random since these are human phenomena only. “For incidents to occur, offenders and their targets – the victims and or property – are required to exist at the same location for a period of time” (Akpinar, 2005). The spatial distribution of crime is considered to be related to a variety of socio economic and crime opportunity factors (Wang et al., 2013). Crime is not something that goes away easily. Actions must be taken to reduce crime incidents for crime prevention. One important step for crime prevention is to analyze the current situation like determining areas of high crime concentration, which of the crimes are occurring more frequently than other crimes, but a big volume of crime data has made the process of analyzing crimes difficult (Nasridinov and Young-Ho, 2014). Analyzing the crime pattern and controlling it using various techniques has become possible using spatial information technology. The whole dynamics of crime analysis and mapping has started changing with new technologies. The traditional method of maintaining criminal records has become obsolete. It is not adequate for the requirements of today’s crime scenarios. It does not provide an accurate, reliable solution for decision support. It does not provide real-time data required for quick decision support. The law enforcing authorities previously faced a very hard situation, controlling the crime, as they had very limited resources compared to resources, which modern crime fighters’ use now a day. The solution to this increasing problem is to make meaningful utilization of information technology with the understanding of spatial patterns of crime incidences.

Geospatial technology with new methods and tools can play vital role in the mapping and analysis of crime. It supports better synoptic perspective to crime study, analysis, mapping, proactive decision making and prevention of crime (Balogun et al., 2014). Mapping of crime and related factors that affect the safety of people can be helpful to police for protecting citizens and are also used to raise people’s awareness regarding the dangerous locations (Tahani et al., 2015). The locations where crimes most commonly occur can easily be visualized by mapping and based on that resources can be effectively utilised. It can empower the law and enforcement agents with the analysis and visualization of the crime patterns, help understand relationship among different crime events and predict future crime incidents. It can be used to further identify factors contributing to crime, and thus allow police to proactively respond to the situations before they become problematic (Thangavelu et al., 2013). Danny (2015) presented a geospatial approach for crime mapping and attendant management in the enhancement of tight security using time series analysis in Asaba, Delta State, Nigeria. Jorge et al., (2012) combines statistical methods and spatial models to strengthen the Intelligence-Led Policing (ILP) methods to provide the necessary tools for Decision Support System (DSS) of police departments. On the other hand, in other few studies, spatial statistics were employed to quantify the relationship between features of the remote sensing images and crime events on the ground, and these analyses may be particularly useful as input to policy decisions about policing within the community (Chen et al., 2015). A study on crime was reported to identify the spatio-temporal pattern in Dala L.G.A of Kano State, Nigeria (Mohammed and Salihu, 2013). Recently one study has used a density map of crimes with kernel method to predict the burglary crimes based on current situation (Gamze et al., 2018). It was concluded that it could be applied for other security and intelligence related applications. On the other hand, another study (Kounadi et al., 2018) developed population models to depict the spatial distribution of people who have a heightened crime risk for burglaries and robberies. This was reported very effective for carrying out crime analysis more precisely and which can provide accurate information about crime rates to the public. In a study by Snyders et al., 2018 carried out in two neighborhoods, Queenswood and Kilner Park, in the north-east of the City of Tshwane of South Africa on the specific crime patterns and fear of crime, it was concluded that the use and avoidance of places in the neighborhood do not always relate to the local crime hot-spots.

Identification of crime hot-spot in the spatial domain is one of the important aspects of crime mapping and analysis to take up more decisive steps to minimize crime incidents. A number of studies have been conducted on the crime hotspot analysis (Jaishankar et al., 2009; Kumar et al., 2012; Ansari and Kale, 2014; Saravanakumar and Revathy, 2016; Achuand Suja Rose, 2016; Ahmad et al., 2018). Achuand Suja Rose (2016) presented hotspot analysis where Moran'sindex (*m*) test statistic of spatial autocorrelation has been done prior to Getis-Ord *Gi** hotspot analysis to find out the clustering pattern as well as the outliers in the data. Recently, an effective crime analysis was reported where Voronoi diagrams (VDs) were employed in spatial analysis (Melo de et al., 2017; Melo de et al., 2018). It was found to recognize crime patters associated with crime concentration, crime along pathways, and the highly regularized distribution of crime in spatially limited areas. CrimeStat was another spatial statistical program for the analysis of crime incident locations (Levine, 2017). It can interface with most desktop GIS programs to provide hotspot analysis as well as other statistical tools. This was mainly used to assist the law enforcement agencies and criminal justice researchers in their crime mapping efforts.

Most of the hotspot analysis studies have been conducted based on the spatial autocorrelation of the crime incidents considering the fixed threshold distance. It affects the intensity of the spatial clustering and sometimes provides poor spatial autocorrelation. In this work, incremental spatial autocorrelation was employed to address this issue more effectively to find a better correlation among the hotspots with the higher *z*-score. The *z*-score is the measurement of the standard deviation which implies how the dataset dispersed from the average value. The *p* or probability value determines if the observed spatial pattern is the outcome of the random event (higher *p-value*) or it has some statistical significance (lower *p-value*). A higher *z*-score and smaller *p*-value of a feature specify spatial clustering of a higher degree. A number of studies on crime have been done using Geomatics worldwide including India. Perspective view on crime mapping was effectively presented using multi-temporal data of crime for a few major cities of India (Ahmad et al., 2017). This can help in assessing the crime trends in the spatial domain. A similar study was done by Ahmad et al. (2018) using geospatial technology for the Jharkhand state of India to understand the crime trend. Crime GIS was implemented for Chennai city policing to strengthen the policing the activity with the spatial crime analysis tool (Jaishankar et al., 2009). A number of spatial platforms have been developed for the operational activity of crime for better management. However, there is lack of detailed study for understanding crime hot-spots in the North-Eastern part of India till now. The present work has following major objectives-

a. Hotspot analysis using incremental spatial autocorrelation on temporal crime incidents reported during last the three years.
b. Understanding the type of reported crimes incidents occurred during different times of the day.
c. Understanding the pattern of crime hotspots over population density.

2. Study area

Shillong known as Scotland of India is a hill station and the State capital of Meghalaya. It is also the district Head Quarters of East Khasi Hills of Meghalaya situated at an average altitude of 1500m above mean sea level. Shillong is spread around 64.36 square km with a population of 143,229 according to Census 2011 with an average sex ratio of 1042. Shillong city is divided into 27 wards under a Municipal board with 7 police stations. Shillong is well connected by roads with all major North Eastern States of India. National Highway 40 is the lifeline of the city as it connects Shillong with Guwahati, the gateway of North Eastern States. Another National Highway 44 connects the city with Tripura and Mizoram and touches the International border with Bangladesh. The study area with the ward boundary and location of police stations overlaid on the Cartosat-1 satellite imagery is depicted in figure 1.

Recent crime statistics have shown that despite being a popular tourist destination in North East India, Shillong has a high crime rate. Although the employment ratio and literacy rate are higher in the city area, the outskirts of the city are still facing lower employment status with low literary rate. In the past few years, trespassing, murder, crimes against women, theft and cheatingrate are rising. The location of crime incidents occurred during 2014-2016 overlaid with the location of police stations and ward boundary are depicted in figure 2 and year-wise details given in figure 3.

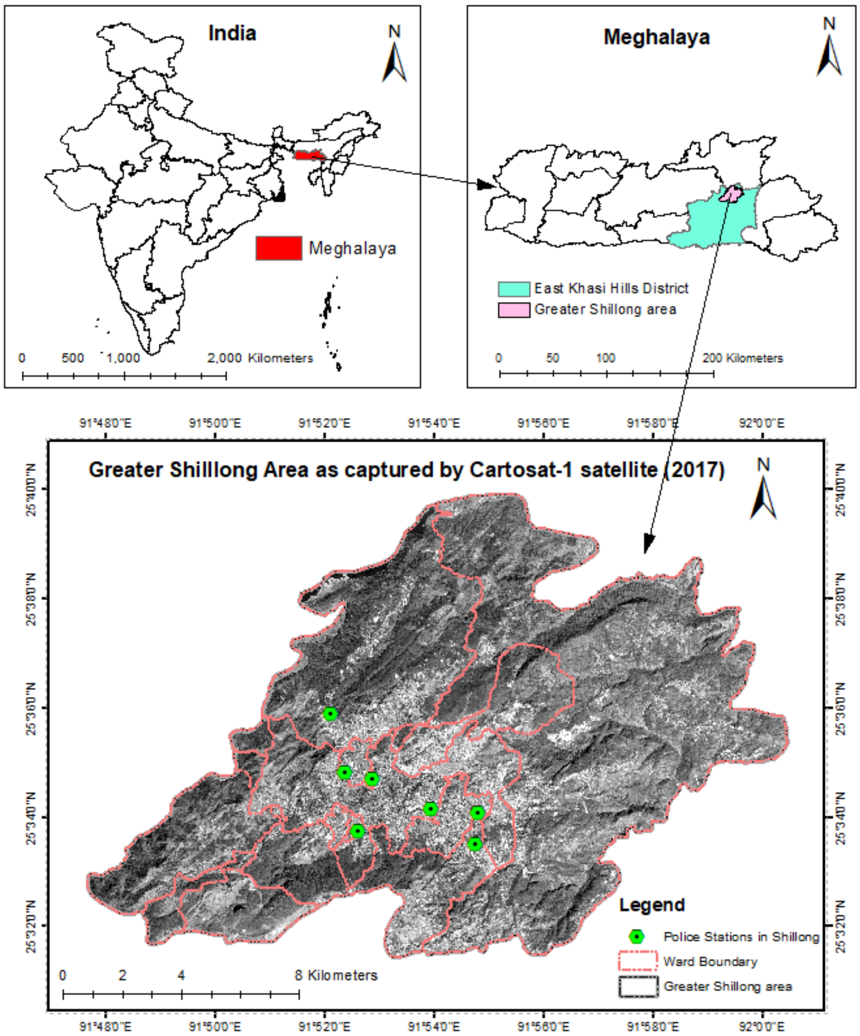

Figure 1: Shillong area as viewed by Cartosat-1 satellite data

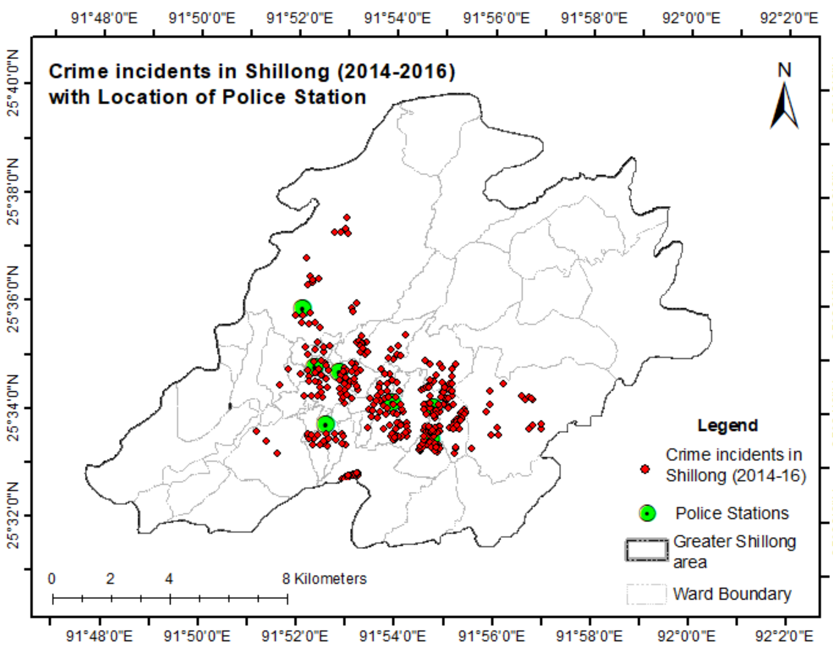

Figure 2: Location of crime incidents occurred during 2014-2016

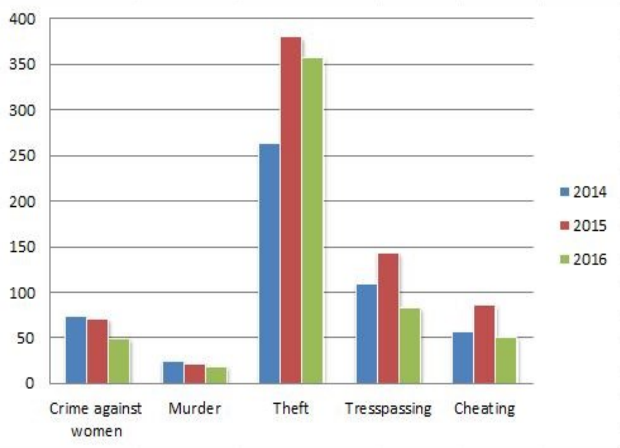

Figure 3: Category wise distribution of crime in three years (2014-2016)

However, Shillong is also known as a safer place for visit among all the tourist places of NE States. Increasing crime rate can hamper the lives of the common people as well as the tourist business. Security system from any place signifies the overall growth and prosperity. So the policing system must be organized and resourceful for good management of crime monitoring. To strengthen the police resource system and analyzing the current crime patterns in the city, we have selected Shillong as our study area

3. Data and Methodology

3.1 Datasets used

Crime incident comprised of 4515 records reported during the last three years 2014-2016 collected from the concerned Authority of the District Administration for analysis. Various crimes registered under the police stations under the Indian Penal Code (IPC) have been categorized in 5 major types in trespassing, murder, crimes against women, theft, and cheating. Existing base map such as roads, settlements as per census 2011 has been overlaid along with administrative GIS data, such as the ward boundary of Shillong city and police stations for better visualization and interpretation of crime incidents, already generated by North Eastern Space Applications Centre, Department of Space, Government of India, Umiam-Shillong, Meghalaya, India.

3.2 Preprocessing of crime incident data

Crime incident records received from the concerned authority comprises of spatially distributed point data. As the crime data have shown that multiple incidents have occurred within a short distance of one another, so the intensity of the crime incidents at every single location was measured by the Integrate and Collect event tool of ArcGIS 10.1 software:

Integrate – To snap features within a specified distance or given X, Y tolerance of each other and makes those features coincident or identical. It performs the followings task (ESRI Tool reference):

- Vertices lying within the X, Y tolerance of one another will be assigned the same coordinate location.
- When a vertex of one feature is within the X, Y tolerance of an edge of any other feature, a new vertex will be added on the edge.
- When line segments intersect, a vertex will be added at the point of intersection for each feature involved in the intersection.

It is recommended not to use high tolerance value as it may delete a number of polygons or lines which in turn may not produce good results The choice of value for the X, Y tolerance is critical. This tolerance value can be determined based on the characteristics of the crime data; how densely incident locations are spatially located. After analyzing the three years data with different ranges of the X, Y tolerance, it was observed that the optimal range of X, Y tolerance lies between 200m to 270m as the crime incidents records are comprised of spatially distributed point data.

Collect Event – Integrated crime incident points resulted in the previous step were used for the operation of collect event. It creates the incident points to a set of weighted point data by creating a new feature dataset of the previous one with an additional field to indicate the number of incidents at each location within a specified snapping distance.

3.3 Methodology

The proposed methodology is based on spatial statistical analysis. Simple interpolation tools like inverse distance weighted (IDW) and natural neighbor interpolation may not help in hotspot analysis of crime as they can only estimate the resultant surfaces without statistical significance. Similarly, interpolation techniques like spline and trend are not suitable for hotspot analysis. Statistical interpolation technique like Kriging is well established in geostatistics, however, this has been found suitable for the study related to soil or geology where there is a big gap between the samples and there is a spatially correlated distance or directional bias in the data (Deshmukh and Anappa, 2018).

The proposed method is composed of two parts, i.e. i) Incremental spatial autocorrelation using Moran's index (Moran 1950), ii) Hotspot analysis using Getis-Ord Gi* (Getis and Ord, 1992). Appropriateness of the both techniques in the context of crime analysis are illustrated below with statistical details.

i) Incremental Spatial autocorrelation: It measures the correlation of a feature expressed in clustered or dispersed. The strength of the correlation is determined at different distances where the clusters are prominently formed. Statistically significant peak positive z-score indicates distances where spatial processes promoting clustering are most pronounced. It can be computed using Moran's index (*m*) (Saravanakumar and Revathy 2016) which can be defined as follows:

$$m = \frac{n}{A_0} \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{i,j} z_i z_j}{\sum_{i=1}^{n} z_i^2} \quad (1)$$

Where z_i is the deviation of an attribute for feature m from its mean $(x_i - X)$, $w_{i,j}$ is the spatial weight between feature m and j, n is equal to the total number of features, and A_0 is the aggregation of all the spatial weights.

$$A_0 = \sum_{i=1}^{n} \sum_{j=1}^{n} w_{i,j} \quad (2)$$

The z_m -score for the statistic is computed as:

$$z_{Im} = \frac{m - E[m]}{\sqrt{V[m]}} \quad (3)$$

where, $E[m] = -1/(n-1)$ is the expected value under the null hypothesis with no spatial clustering and $V[m]$ is the variance which measures variability of the numbers from their mean value which can be computed as

$$V[m] = E[m^2] - E[m]^2 \quad (4)$$

The distance is one of the important criteria for receiving better results in hotspot analysis. It must ensure that all the spatially distributed incident points should have at least one neighbor. It is difficult to approximate the reliable set of neighbors for each incident point without defining the appropriate distance threshold between them. That is why; it has been suggested to use incremental autocorrelation in hotspot analysis where the intensity of spatial clustering of crime incidents is obtained effectively by the *z*-score measured by increasing the distance band or threshold distance. The distance corresponding to the higher *z*-score obtained at the peak is treated as a threshold distance for hotspot analysis as it reflects the more accurate formation of the cluster.

ii) Hotspot Analysis using Getis-Ord G_i*: Based on the threshold distance defined in the equations (Eq.1-Eq. 4), hotspot analysis indicates the locations with statistically significant hotspots and cold spots in the aggregated data that are within a proximate region on a calculated distance. It needs clustering in the data and returns *z*-score to indicate whether any clustering is present or not in the data. It creates clusters of features with similarly high or similar low values in the cluster. For a significant hotspot, *z*-score should be high and probability (*p*-value) should be low. On other hand, negative, low *z*-score with small probability value indicate a coldspot.

Here, Getis-Ord G_i* statistics is used to identify statistically significant hotspot or coldspots from a set of weighted features and can be defined as

$$G_i^* = \frac{\sum_{j=1}^{n} w_{i,j} x_{i,j} - \overline{X} \sum_{j=1}^{n} w_{i,j}}{S \sqrt{\frac{[n \sum_{j=1}^{n} w_{i,j}^2 - (\sum_{j=1}^{n} w_{i,j})^2]}{n-1}}} \quad (5)$$

where x_j is the attribute value for feature j,$w_{i,j}$ is the spatial weight between feature i, and j, and n is equal to the total number of features and:

$$\overline{X} = \frac{\sum_{j=1}^{n} x_j}{n} \quad (6)$$

$$S = \sqrt{\frac{\sum_{j=1}^{n} x_j^2}{n} - (\overline{X})^2} \quad (7)$$

The final outcome of the G_i* method is a feature dataset containing the cluster of hotspots and coldspots of crime incidents with corresponding G_iZ-score and G_iP-value. The higher the G_iZ-score, clustering of features with high value become more intense which creates the statistically significant hotspots as well as smaller the statistically significant negative *z*-score, clusters of features surrounded by lower values become prominent which is referred as cold spots.

In most of the experimental instances of hotspot analysis, it was observed that the hotspots are defined by hard boundary based on the statistical significance of the cluster. However, some of the important neighboring incidents are not represented in the hotspots. Spatial interpolation technique can address this issue by predicting such incidents based on the G_iZ-score. Here the IDW method is used to interpolate the hotspots and coldspots points for better representation in spatial domain. It assumes the prediction surface which is more influenced by the nearby points than the points in the distant location. The cell size of the output raster is calculated from the shorter of the width or height of the study area extent divided by 250, where the extent is in the output coordinate system specified in the environment.

4. Results and Discussion

Hotspot analysis on crime incidents is reported based on the two spatial statistical methods; spatial autocorrelation using Moran's index (*m)* to measure the correlation of crime incidents expressed in clustered or dispersed and Getis-Ord G_i* statistics to indicate the significance of hotspots or coldspots. Considering the spatial distribution of the crime incidents over a typical topographical terrain like Shillong city of Meghalaya spatial correlation was computed based on the incremental distances to find out the threshold optimal distance with a higher z-score which is required for the best results from Getis-Ord G_i* statistics.

4.1 Statistical analysis on crime hotspots

In this study, three years of crime incident data (2014-2016) comprising of more than 4515 incidents are analyzed and categorized mainly in 5 major types, such as trespassing, murder, crimes against women, theft, and cheating. The analysis was also done for each of the years to see the crime pattern from 2014 to 2016. The *z*-score achieved at different distances during the incremental spatial autocorrelation of three years data was plotted in figure 4. It was observed that the peak *z*-score (= 4.7) was achieved at a distance of 1500m. The z- score achieved at different distances are also given in figure 4.

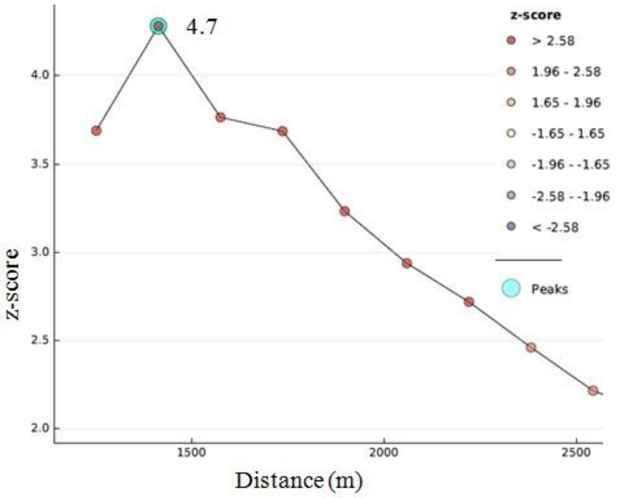

Figure 4: The peak z-score resulted at a distance of 1500m during incremental spatial autocorrelation

Similarly; we have achieved a z-score of 4.2 for 2014 crime incidents, 5.1 for 2015, and 4.5 for 2016 crime incidents. In all the cases, only one statistically significant peak was observed. These threshold distances are an important input to the hotspot analysis. The resultant G_iZ-scores and G_iP-values in Getis-Ord G_i* represent whether crime incidents are with either high or low-value cluster spatially. The highest and lowest scores of G_iZ achieved for four sets of crime incident data, i.e. incident records of 2014, 2015, and 2016 and three years combined (2014-2016) datasets are given in table 1**.** It is observed that G_iZ score was found higher in the hotspot analysis of combined 3 years data with 3.68 as compared to the other yearly recorded crime incident datasets. However, an incident with a higher GiZ score may not form statistically significant hotspots unless it is surrounded by other incidents with higher values. Z-scores are representing these standard deviations where very high or very low (negative) values are associated with very small p-value (probability). The p-value against each of the G_iZ-scores with less than or equal to 0.05 contributes statistically significant hotspots with more than 95 % confidence level. Hotspots in the form of crime density using IDW interpolation based on the G_iZ score is presented in figure 4 for the crime incidents record of 2014. Similarly, crime Hotspot analysis was carried out for the year 2015, 2016, and three years combined datasets are presented in figures 4-6.Here, hotspots are analyzed for each and every year separately and combined. From all the figures it was observed that the crime hotspot coverage (represented in red color in the figures) is comparatively higher in 2014 with minimal coldspots coverage represented in blue color. It is prominent that some of the hotspot areas in 2014 became the crime hotspots of average density in 2015 and again changed in 2016. Though in the year 2015; the crime occurrence rate was higher than the other two years, some areas faced more frequent crimes than other parts of the study area. Because of that, the yellow marked areas of 2015 have shown some visual changes when compared with 2014 and 2016 figures. These yellow marked areas in crime map of 2015 inference that other than the central city, crimes happened in the outer zone are statistically insignificant.

However, the pattern of crime density of 2014 (Figure 5) has a similarity with 2016 (Figure 7). On the other hand, the pattern of crime density of the year 2015 (Figure 6) does not have much similarity with 2014 and 2016 crime maps. Figure 6 indicates that most of the crime incidents occurred in the central part of the city during the year 2015 as compared to the years 2014 and 2016. Figure 8 indicates that crime risk zones generated from all three years of data of the study area. It was observed that the hotspots were also confined in the central part of the Shillong, and this was contributed by the crime incidents taken place during the year 2015. On the other hand, a large number of distinct cold spots are also noticed in most of the instances while hotspots analysis was carried out for all the years' together (Figure 9).

Table 1: Getis-Ord G_i* statistics achieved on different crime incident datasets against threshold distances

Serial No	Crime incident datasets	Number of incidents	G_iZ-score		G_iP-value	Threshold distance (m)
			High	Low		
1	Incidents of 2014	1083	2.71605	-1.2908	0.000600	1456
2	Incidents of 2015	2195	2.85133	-1.3585	0.000081	1205
3	Incidents of 2016	1245	3.41776	-1.63274	0.000014	1649
4	Incidents of 2014-16	4523	3.68501	-1.58792	0.000230	1500

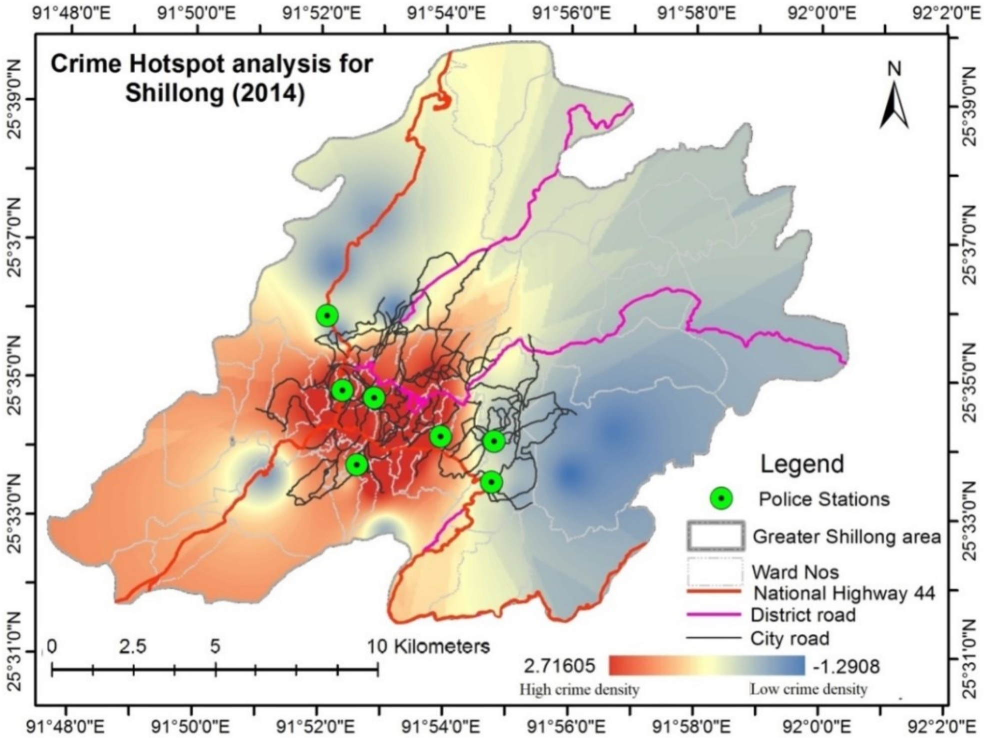

Figure 5: Hotspot in the form of crime density for 2014 crime incident dataset of Shillong city

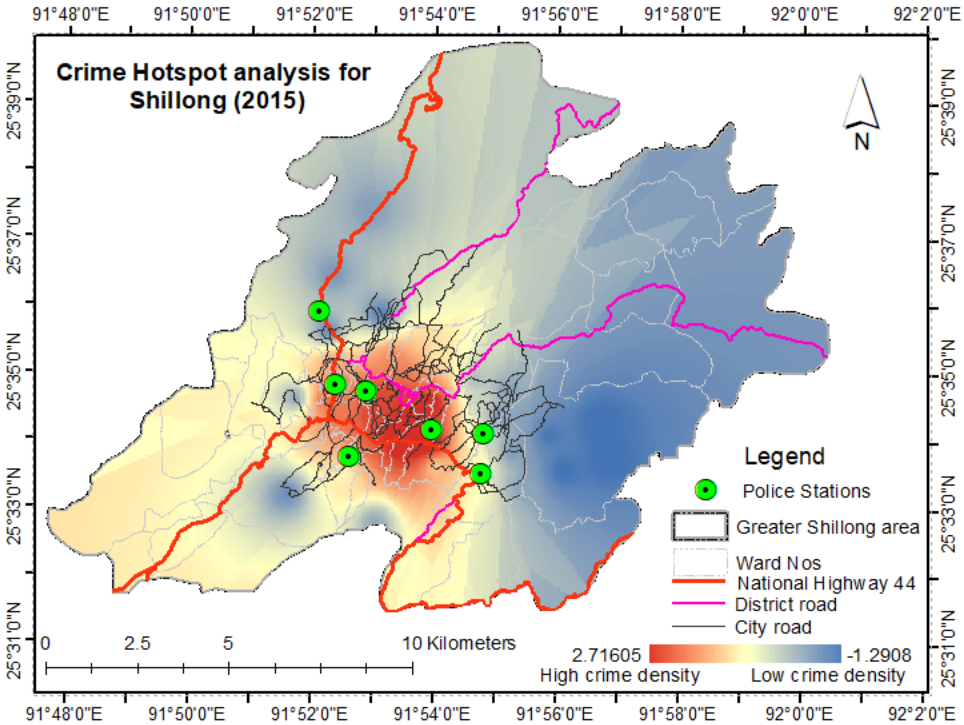

Figure 6: Hotspot in the form of crime density for 2015 crime incident dataset of Shillong city

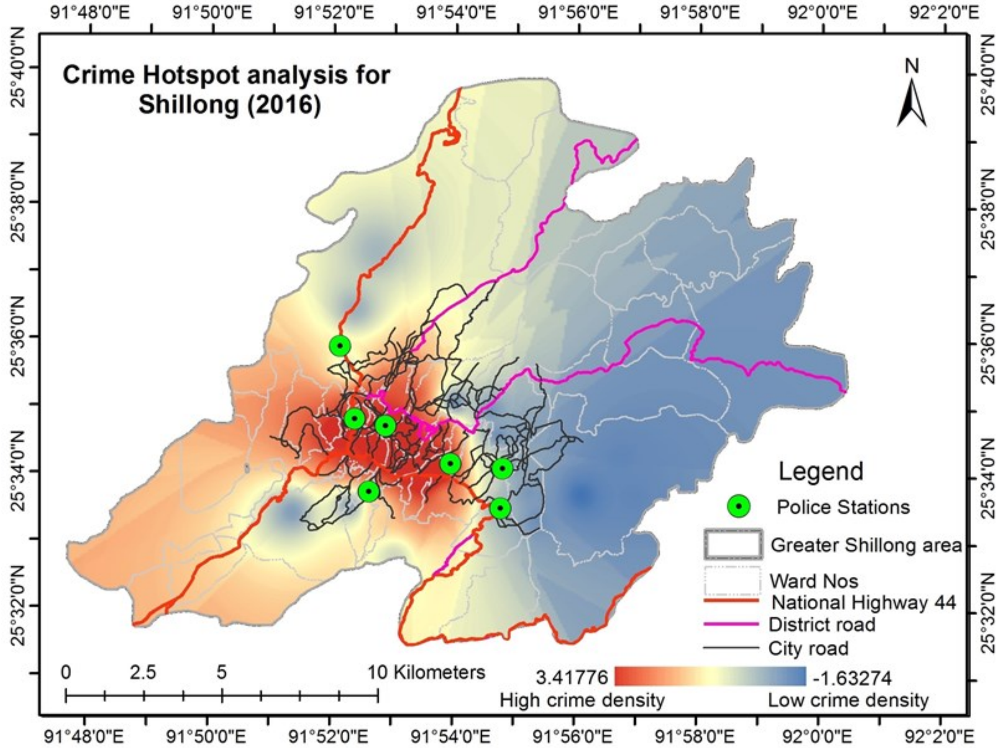

Figure 7: Hotspot in the form of crime density for 2016 crime incident dataset of Shillong city

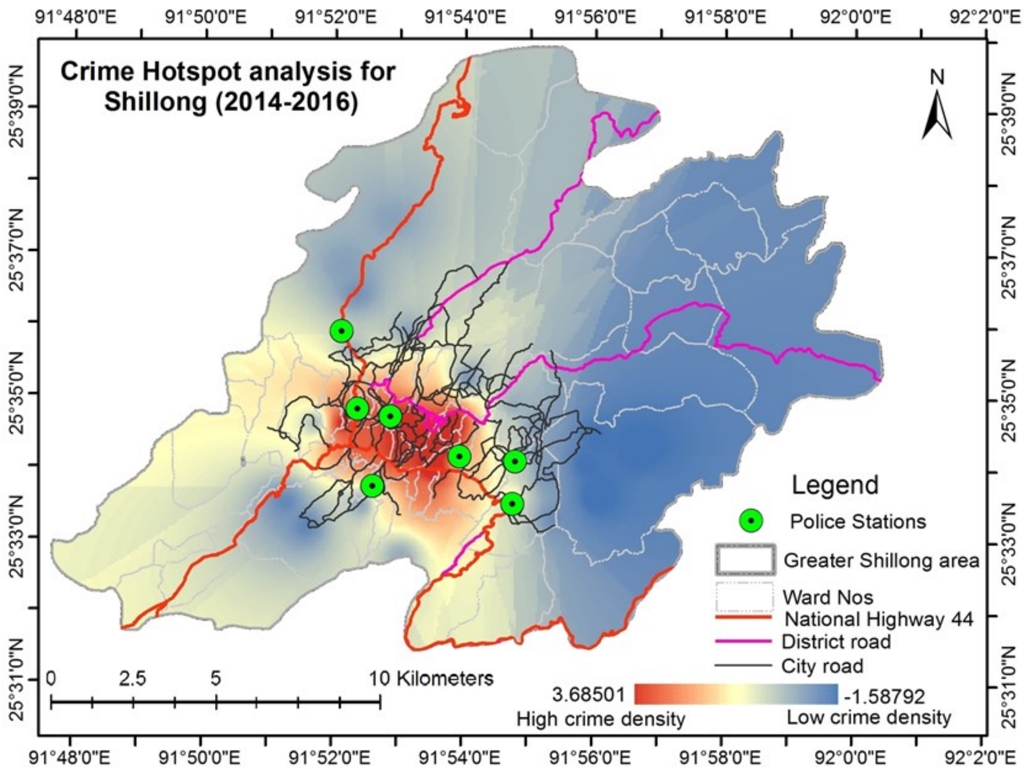

Figure 8: Hotspot in the form of crime density for 2014-2016 crime incident dataset of Shillong city

4.2 Patterns of crime incidents with time

The type of highest number of crime incidents registered during 2014-2016 was theft-related charges (Figure 2). It was highest in 2015 followed by 2016 and 2014, interestingly the highest number of theft-related cases occurred after 20:00 hrs and it reaches to its peak during 22:59-24:00 hrs. The number of crime incidents against each of the crime types registered in a different time periods is graphically presented in figure 9. The cases related to crime against women were occurring in higher rate during evening time (18:00 hrs.-20:00 hrs.). Other crime cases like cheating, trespassing, and murder related charges are not following any pattern with respect to time of occurrence. The human ecological character can often describe the relationship between time of occurrences or temporal behavior of such crime and the offender. As here crime mapping has been done focusing on the spatial character of the incidents happening, temporal analysis of crime incidents is beyond the scope of this paper.

4.3 Crime hotspots over population density

The spatial distribution of crime hotspot is associated with different types of socio-economic factors. In a world scenario, most of the crimes have occurred in highly populated areas. A population density map based on census 2011 data has been prepared. Crime hotspots (2014-2016) of the Shillong area overlaid on population density and existing police stations are given in figure 10. The crime density in each ward with their population density is given in table 2. It was observed that most of the crime hotspots appeared in those wards where population density is 10,000-20,000 per square kilometer. Interestingly crime hotspots were not observed in highly populated areas like Mawkhar and Jaiaw. Some of the hotspots (average) were found unevenly distributed over space irrespective of the size of the population density. For example, some of the areas with very less population density (500-2000) like Madanryting, Laitkor, and Pynthorumkhra are also found as crime hotspots (table 2).

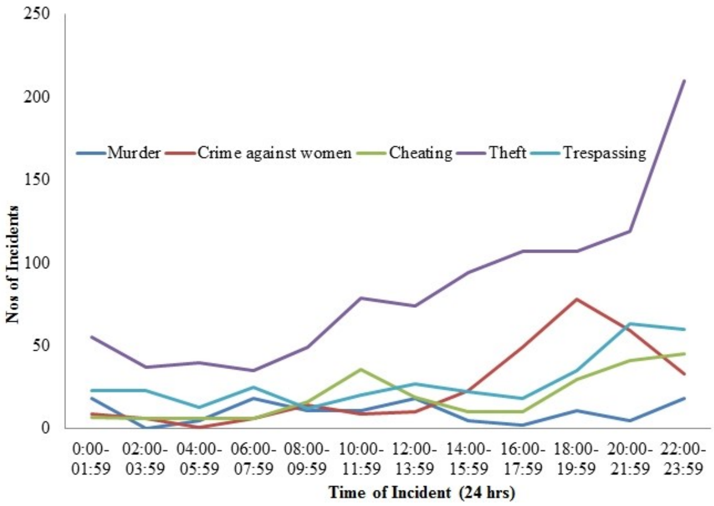

Figure 9: Number of crime cases registered in different time interval of the day

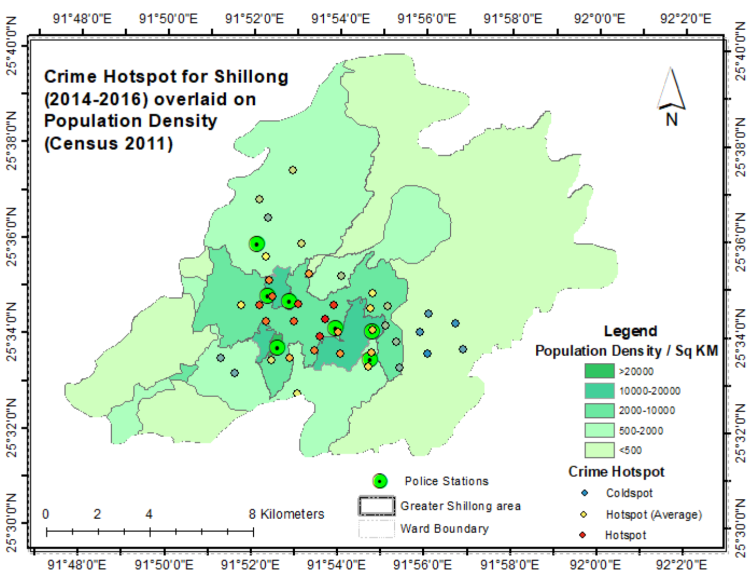

Figure 10: Crime hotspots of Shillong (2014-2016) over Population density

Table 2: Ward-wise Population density versus crime density

Ward name	Population Density/Sq km	Crime density
Mawkhar, Jaiaw, Jail Road, Laban, Malki	>20000	Average
Kench's Trace, Nongthymmai, Police Bazar	10000-20000	High
European Ward, European Ward, Jail Road, Laitumkhrah, Lumparing, Mawprem, Shillong Cantonment, 3rd Mile 5th Mile Laitumkhrah, Mawprem, Nongkseh, Rynjah, LapalangUmlyngka, Umpling	2000-10000	High
6th Mile, Kriet , Laitkor, Mawpat, Nongpiur, 4th Mile, Lawsohtun, Madanryting, Mawlai, Pynthorumkhrah	500-2000	High
Mawdiangdiang, Mawinaglah, Mawklot, MawlongMawpynthih, Mawtawar, Nongrah, Nongsawing, NongumlongSyllaiulur,Umsawli,Umshing Village	<500	Low

5. Conclusion

Spatio-statistical technique for analysis of crime hotspots in Shillong city, Meghalaya, India has been found to be extremely useful in understanding, mapping and predicting crime hotspots. The entire approach is based on a statistical method using Moran's index (m) and Getis-Ord G_i*. It involves deriving spatial distribution of patterns of crime with a higher confidence level based on optimal ranges of values of *z*-score and *p*-value with an appropriate threshold distance. It has been demonstrated that deriving threshold distance using incremental spatio autocorrelation can enhance the predictability of the crime hotspots.

The study identified the crime hotspots in the city with the occurrences of various types of crime occurred in different time periods of the day. It was observed that the hotspots were primarily confined to the central part of the city and some of the hotspots (average) were unevenly distributed over space irrespective of the size of the population density. The crime against women were reported mostly during the evening and the highest theft were reported after 2200 hrs during night. Other crime cases were not observed with any specific pattern concerning the time of occurrences.

It is difficult to achieve optimal values of crime statistics simultaneously for deriving the spatial distribution of crimes based on actual incidents. However, machine learning techniques could be explored for better analysis of hotspots as well as prediction for the coming year based on more time-series data.

Acknowledgements
The authors would like to thank the Office of the Superintendent, Shillong, Meghalaya for sharing of crime data of the period 2014-2016 for analysis in the reported work.

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