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SPATIAL TEMPORAL ANALYSIS OF RURAL CRIME HOT SPOT ZONE USING GIS: A PART OF COIMBATORE

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ABSTRACT

Spatio-temporal analysis is one of the suitable method in crime analysis. It is ability to visualize the spatial patterns and control emotionally over a time-ordered sequence of spatial variation. It has been involved the spatial modeling and models of location-allocation, spatial interaction, spatial choice with search, spatial optimization and space-time. Spatio-Temporal Analysis of Crime (STAC) is a powerful tool to identify the crime patterns and detect the crime hot clusters in identifying the hotspot areas. The aim of the objective study is to analyze the spatial effects based on space and time difference among the divisions (space and time) and rate of change. The different types of crime occurrence data were collected from fourteen rural police jurisdiction (2003-2006) in Coimbatore district, TamilNadu. For this analysis, crime occurrence data were used through ArcGIS 10.2 version. The study was analyzed the random walk incidences, and moving path of the peak incidences which are effective models used for entire surrounding area. The study was concluded that spatial-temporal dimension of crime in rural police jurisdictions and explaining how these outcomes used to assist the advance development of crime prevention strategies.

Keywords: Crime, Coimbatore, GIS, Space, Time.

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1. INTRODUCTION

Spatio-temporal crime mapping originated as time geography to understand limits on human activity and imposed by space and time (Miller, 2005). Spatio-temporal crime analysis and mapping system (STCAMS) was technologically advanced for crime analysis by police considering the fact, crime occurs at various locations both in space and time. The police commanders identifying the emerging hotspots, crime trends and patterns of crime activities, which in turn provides useful information to efficiently allocate resources for crime prevention (RatCliffe and McCullagh, 1998). Crime forecasting is scrutinized in three different concepts such as spatial, temporal and spatio-temporal. Spatio-temporal crime forecasting is knowledge of the geographers and crime analysts, which includes methods from econometric modeling to neural networks (Hirschfield and Bowers, 2001). Police organization adapted the processing of computer mapping along with information technology.

Spatio-Temporal Analysis of Crime (STAC) is a computer program developed by the Illinois criminal justice authority as a clustering algorithm, which determines the area with highest density of incidents and used the algorithm to calculate a hot spot boundary (Levine, 2002). A number of police departments lead the nation in the computing mapping of crime and crime analysis. Spatial pattern analysis used in recognition methods (Block & Block, 1995; Hirschfield *et al*., 1995; Johnson *et al*., 1997; Rengert, 1997; Canter, 1998; Eck, 1998). Diggle *et al*., (1995) have developed a test to determine the space-time interaction as general phenomena in a data set. The huge investigation challenges were related to five aspects such as to be exact the nature of geospatial data, the need to formalize a theory of the form of representation, to consider the purpose of the representation, to understand the needs of the user and familiarization with the tools and technology involved in different visualization methods (Fairbairn *et al*., 2001).

Police organization adapted the processing of computer mapping along with information technology (Weisburd, 2001). Mapping crime hot spots were applied to general crime analysis (Rich, 1995 & 2001; Canter, 1998; LaVigne and Wartell, 1998; Harries, 1999), vehicle crime analysis (Rengert, 1997; Ratcliffe & McCullagh, 1998), serial crime investigations (Rossmo, 1995; Cook, 1998; Hubbs, 1998) and gang activity (Kennedy *et al*., 1998). Crime hot spot techniques have the capability in computer programming to analyze the STAC and all the analyses were determined to the point data-sets of higher intensity.

Distribution of crime locations changes with time. A number of studies developed for the tools which incorporate a temporal dimension to the analysis of crime pattern. Dynamic visualization is used for the spatio-temporal mapping (Koussoulakou & Kraak, 1992; Shepherd, 1995; Dykes, 1996; Andrienko *et al.*, 2003). Several different techniques was available in determine hot spots spatially, STAC (Block, 1995) techniques implemented in the CrimeStat II software (Levine, 2002) produced the results are most useful in focusing the hot spots. For identifying the temporal distribution of crimes, it has to measure the determination of the time at which the event occurred.

Hotspot policing proceeds achieved importance as a prepared method specifically in intelligence-led policing (Audit Commission, 1993; HMIC, 1997; Smith, 1997; Heaton, 2000; Maguire, 2000; Ratcliffe, 2002) and the growth of both intelligence and crime analysis practice (Andrews and Peterson, 1990; Carter, 1990; Gottlieb *et al.*, 1998). In the period of economic construction, both crime prevention practitioners and police locate appeal in a method that allows them to focus resources on the areas of need and to have a process for explaining their objective decision-making to others.

Contributions by geographers to the study of crime have been recent origin, although the literature is now growing rapidly. The geographers have more interested in crime studies (Philips, 1972; Scott, 1972; Pyle, 1974; Smith, 1975; Capone and Nicholls, 1975; Davidson, 1975; Herbert, 1976). However, the geographical study of crime is a long way short of delimiting the true extent of the field. Several geographers have observed (Lottier, 1938; Cohen, 1941) that spatial patterns of the homes of offenders and ecological association between the variety of social housing and demographic conditions. The innovative attention in crime among geographers, and current theoretical developments in criminology, makes an opportune time to consider some suggestions conserving methodology. These may also be relevant to the geographical analysis of other social problems.

The processing functions of the system are broadly grouped into three functional areas as computer mapping, spatial database management and cartographic modeling (Chang, 2002). Geographical information system (GIS) is to monitor, detect and communicate the trends of thefts. GIS was used the conjunction with an up to date digitized police boundary map and moderately user pleasant computer package to scrutinize such data. Fixed and random effect model were used for Coimbatore rural police jurisdiction in spatial temporal analysis. The major objective of the study is to analyze the spatial effects based on space and time difference among the divisions (space and time) and rate of change.

2. Study Area

Coimbatore is popularly famous as 'The Manchester of South India'. The total geographic area of the district is 105.60 sq.km. Coimbatore rural division is situated between 10°68′04″ and 11°16′08″ Northern latitude and 76°68′12″ and 77°15′16″ Southern longitude in the extreme west of Tamil Nadu near Kerala. Coimbatore coordinates rural zones which have been identified by the Development of Police as an area with the high number of crime hits. Rural police jurisdiction were divided into two sub-division such as Perur and Periyanaickenpalayam. The study has been used fourteen police jurisdictions (Sirumugai, Mettupalayam, Pillur, Karamadai, Periyanaickenpalayam, Thudiyalur, Vadavalli, Thondamuthur, Alandurai, Karunya, Perur, Madukarai, Podanur and Kinathukadavu) as shown in Figure 1.

3. Data Preparation

The recorded crime data were collected from Home Affairs Department, Superintendent of Police Office (SPO), Crime Record Bureau (CRB), Coimbatore rural police jurisdiction. Coimbatore District, Tamilnadu. The data were accumulated through the annual record from the year 2003 to 2006. The number of crime recorded totally 1386 from 14 Police jurisdiction in detailed information of locative place, group of crime, type of theft, year, month, date, day, time and offender was available and converted into the database files. The decision was made to use the crime reports to identify the hotspots. The crime record were identified to a single report of criminal activities in the field. The data fields were used to identify the hotspots spatially and temporally the starting date and time of the occurrence, ending date time of the occurrence, address of the occurrence and occurrence type code, which identified the type of crime that was committed. All the details were geocoded and imported into ArcGIS 9.3 version for further analysis.

4. Mapping Methodology

Thematic mapping was prepared for the recorded incidences of Crime for Coimbatore rural police jurisdiction. The mapping was completed to study the neighborhood crime cases and possible risk at neighborhood level. Thematic mapping for the crime cases from the year 2003 to 2006 were superimposed for the spatial variation of crime incidences at Police Jurisdiction level.

4.1. Knox Index

The Knox Index is a simple comparison of the relationship between incidents in terms of distance (space) and time (Knox, 1963; 1964). That is, each individual pair is compared in terms of distance and in terms of time interval. Since each pair of points is being compared, there are N*(N-1)/2 pairs. The distance between points is divided into two groups - Close in distance and Not close in distance and the time interval between points is also divided into two groups - Close in time and Not close in time. The definitions of 'close' and 'Not close' are left to the user. A simple 2 x 2 table is produced that compares closeness in distance with closeness in time. The number of pairs that fall in each of the four cells are compared as shown in Table 1.

Where, $N = O1 + O_2 + O3 + O4$

$S_1 = O_1 + O_2$

$S_2 = O_3 + O_4$

$S_3 = O_1 + O_3$

$S_4 = O_2 + O_4$

The actual number of pairs that falls into each of the four cells is then compared to the expected number if there was no relationship between closeness in distance and closeness in time. The expected number of pairs in each cell under strict independence between distance and the time interval is obtained by the cross-products of the columns and row totals as shown in Table 2.

Where, $E1 = S_1 * S_{3/N}$

$E2 = S_1 * S_{4/N}$

$E3 = S_2 * S_{3/N}$

$E4 = S_2 * S_{4/N}$

The difference between the actual (observed) number of pairs in each cell and the expected number is measured with a Chi-square statistic (equation 1) as shown in Table 3 and Table 4.

$$X^2 = \sum = \frac{(O_i - E_i)^2}{E_i}$$

with 1 degree freedom ---------- (1)

"Close" time ……….. 3.83017 hours

"Close" distance …… 0.17206 m

4.2. Monte Carlo Simulation of Critical Chi-square

The usual probability test associated with the Chi-square statistic cannot be applied the observations are not independent. Interaction between space and time tend to be compounded when calculating the Chi-square statistics. To handle the issue of interdependency, there is a Monte Carlo simulation of the chi-square value for the Knox Index under spatial randomness (Dwass, 1957; Barnard, 1963). If the user selects a simulation, the routine randomly selects M pairs of a distance and a time interval where M is the number of pairs in the data set (M = N* [N-1]/2) and calculates the Knox Index and the chi-square test. Each pair of a distance and a time interval are selected from the range between the minimum and maximum values for distance and time interval in the data set using a uniform random generator. The random simulation is repeated K times, where K is specified by the user.

Based on criminal recorded for 14 police jurisdiction have been identified as a crime zones. The total period of 48 months (Jan 2003 - Dec 2006), the peak intensity of crime was identified and reduced in to a database. Using the mean of distance and time interval, the Knox index was calculated for the entire set of 1386 incidences, a specific median time interval for the mean distance for the entire month. The index was calculated for each month and Chi-square values and their pseudo-significance levels as complied in Table 5.

For error free results we used 1000 random simulations for the incidences of crime for the entire study period. With random distributions, an extreme value could be obtained by chance, hence reasonable out-of points were selected from the limitation. The cut-off values were taken from that approximate 1% and 5% significant level. For instance, Knox index is one tailed test (i.e., only a high Chi-square values is indicated of spatial interaction), as upper threshold level of percent was adopted. Only if the observed Chi-square test for the Knox index is larger than 95 percentile threshold, the null hypothesis of the random distribution between space and time will be rejected.

There are advantages to each of these methods. The mean is the center of the distribution; it denotes a balance point. The median divided both distance and time interval into approximately equal numbers of pairs. The division is approximate since the data may not easily divide into two equal numbered groups. User-defined criteria can fit a particular need of an analyst. For example, a police department may only be interested in incidents that occur within two miles of each other within a one week period. Those criteria would be the basis for dividing the sample into 'Close' and 'Not close' distances and time intervals.

4.3. Mantel Index

The Mantel Index resolves some of the problems of the Knox Index. It is a correlation between distance and time interval for pairs of incidents (Mantel, 1967). The general test of the correlation between two dissimilarity matrices that summarizes comparisons between pairs of points (Mantel and Bailar, 1970). Based on a simple cross-product of two interval variables (e.g., distance and time interval):

$$T = \Sigma \sum_{i=1}^{N} \sum_{i=1}^{N} (Xij - \text{Mean } X)(Yij - \text{Mean } Y) \quad \text{.........} (2)$$

Where, Xij is an index of similarity between two observations, i and j, for one variable (e.g., distance) while Y_{ij} is an index of similarity between the same two observations, i and j, for another variable (e.g., time interval).

The cross-product is then normalized by dividing each deviation by its standard deviation

$$T = \Sigma \sum_{i=1}^{N} \sum_{i=1}^{N} (Xij - \text{Mean } X)/sx * (Yij - \text{Mean } Y)/sy)$$

$$T = \sum_{i=1}^{N} \sum_{i=1}^{N} (Zx * Zy/(-1) \quad \text{.........} (3)$$

Where X_{ij} and Y_{ij} and are the original variables for comparing two observations, i and j, and Z_x and Z_y are the normalized variables. If used as an index, rather than an estimate of variance explained, the Mantel Index can identify time periods when spatial interaction is occurring. It can be seen that high correlations between the distance and time of incidences. In Knox index showed four years are non- significance.

4.4. Monte Carlo Simulation of Confidence Intervals

The Mantel index is a Pearson product-moment correlation between distance and time interval, the measures are not independent and, in fact, are highly interdependent. The significance test for a correlation coefficient is not appropriate. The Mantel routine offers a simulation of the confidence intervals around the index. If the user selects a simulation, the routine randomly selects M pairs of a distance and a time interval where M is the number of pairs in the data set (M = N* [N1]/2) and calculates the Mantel Index. Each pair of a distance and a time interval are selected from the range between the minimum and maximum values for distance and time interval in the data set using a uniform random generator.

For each pair of a distance, time interval is selected from the range between the minimum and maximum values for distance and time interval in the data set using a uniform random generator. Since the Mantel Index is a two tailed test (i.e., one could just as easily get dispersion between space and time as clustering), adopted a lower threshold of the 2.5 percentile and an upper threshold of 97.5 percentile. Combined, the two cut-off points ensure that approximately 5% of the cases would be either lower than the lower threshold or higher than the upper threshold under random conditions. In other words, only if the observed Mantel Index is smaller than the lower threshold or larger than the upper threshold will the null hypothesis of a random distribution between space and time be rejected. All time periods has no significant for the year 2003-2006 were presented in Table 5.

4.5. Spatial -Temporal Analysis of Moving Average

The Spatial-Temporal Moving Average is a simple statistic method with moving mean center of *M* observations where *M* is a sub-set of the total sample, *N*. By 'moving', the observations are sequenced in order of occurrence. Hence, there is a time dimension associated with the sequence. The *M* observations are called the span and the default span is 5 observations. The span is centered on each observation as an equal number on both sides. Because there are no data points prior to the first event and after the last event, the first few mean centers will have fewer observations than the rest of the sequence. In brief, the Spatial-Temporal Moving Average simply plots the changes in the mean center of the span and is useful for detecting changes in the behavior pattern of the incidences. Movement of crime incidences in space and time were observed for 1369 locations for a period of 48 months as complied in Table 6 and Figure 3.

4.6. Correlated Walk Analysis (CWA)

(i) Analysis

Correlated Walk Analysis is a tool to analyze the spatial and temporal sequencing of incidents. CWA routine makes guesses about the time and location of a next event, based on both the spatial distribution of the incidents and the temporal sequencing of them. It is a spatio-temporal moving average with a prediction of a next event. The difference between the first and second event is the first interval. The difference between the second and third events is the interval. The difference between the third and fourth event is the interval and so forth. For the each successive interval, there is a time difference; there is a difference and there is a direction. This could be extended to all the intervals, comparing each interval with the next one; i.e., the first interval is compared with the second, the second interval with the third, the third intervals with the fourth, and so on until the sample is complete. Once comparing successive intervals, this is called a *lag of 1.* It is important to keep in mind the distance between an event (e.g., an incidence) and an interval. It takes two events to create an interval. Thus, for a lag of 1, there are M=N-1 intervals where N is the number of events (e.g., for 3 incidents, there are 2 intervals). A lag of two compares every other event. The CWA Correlogram routine calculates the Pearson Product-Moment correlation coefficient between successive events as shown in Figure 2. The random walk model of the peak incidences with a start at the Police Jurisdiction of Coimbatore and terminates near Thudiyalur Police Jurisdiction compiled in Figure 3.

(ii) Diagnostics

The diagnostics routine is similar to the CWA – correlogram except that it calculates an Ordinary Least squares auto regression for a particular lag. That is, it regresses each interval against a previous interval. This analyses the time interval, distance and bearing separately.

(iii) Prediction

Finally, after analyzed the sequential pattern of events, the prediction about the time and place of the next event is made. This is based on the three criteria for making prediction, each with a separate interval:

(a) The mean difference applies the mean interval of the data for the data specified lag to the last event. For example, for time interval and a lag of 1, the routine calculates the interval between each event and takes the average. It then applies the mean time interval to the last time in the data set as the prediction.

(b) The median difference applies the median interval of the data for the specified to the last event.

(c) The regression equation calculates a regression coefficient and constant for the specified lag and uses the data value for the last interval as in put into the regression equation; the result is the predicted value. For the present study the regression equation is used to predict the next event.

The routine takes the time and location of the last event and adds a time interval, a direction, and a distance as the predicted next event (next time, next location). Table 7 shows the predicted time, distance and bearing interval from the last case even 52 (observed) using their regression equation method for a lag distance of 1. For the above analysis, a lag distance of 1 was used and from the analysis the events were predicted for the next month location and time at **X=**

10.92788, Y= 77.01874 and 15-16 hours respectively. A 3-D elevation map is presented as Figure 5 for the spatio- temporal distribution of crime in Coimbatore district rural area and also represents the predicted location at the predicted time of the next incidence occurrences. Table 7 shows that's the regression for the space time analysis where the multiple R^2 = 0.00008. The analysis of variance is presented as shown in Table 8. The predicted values obtained through spatio-temporal analysis for a lag distance of 1 is given as Table 9.

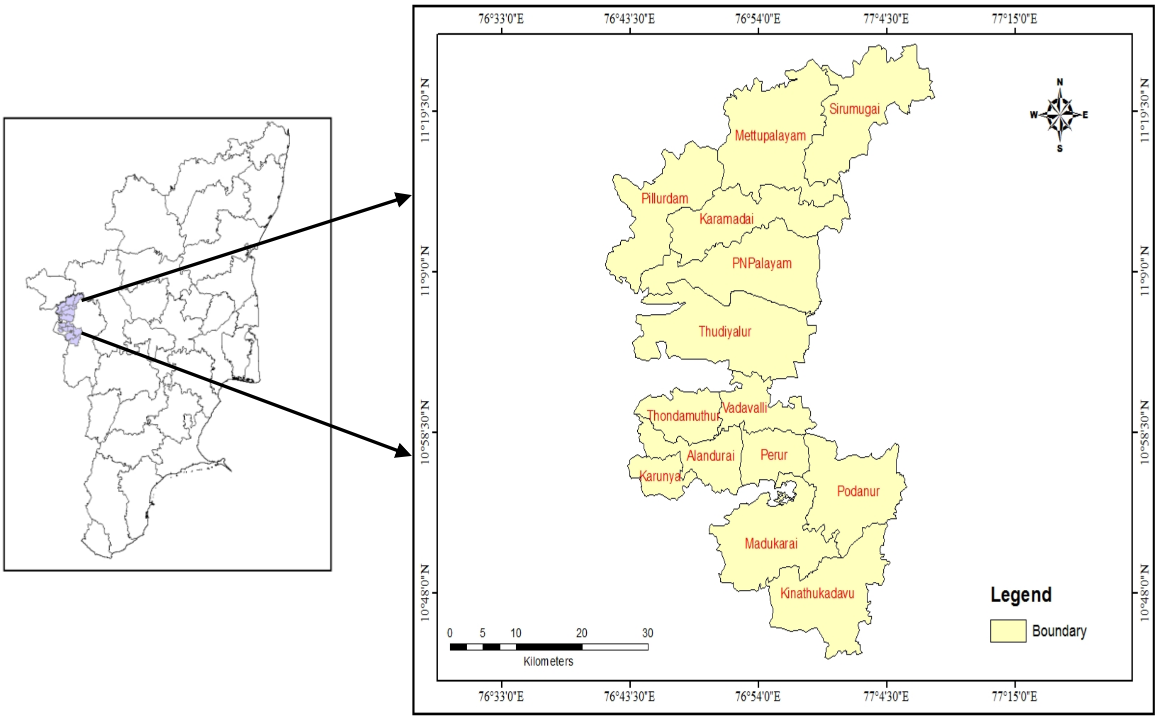

Figure 1. Study area map of Coimbatore rural police jurisdiction

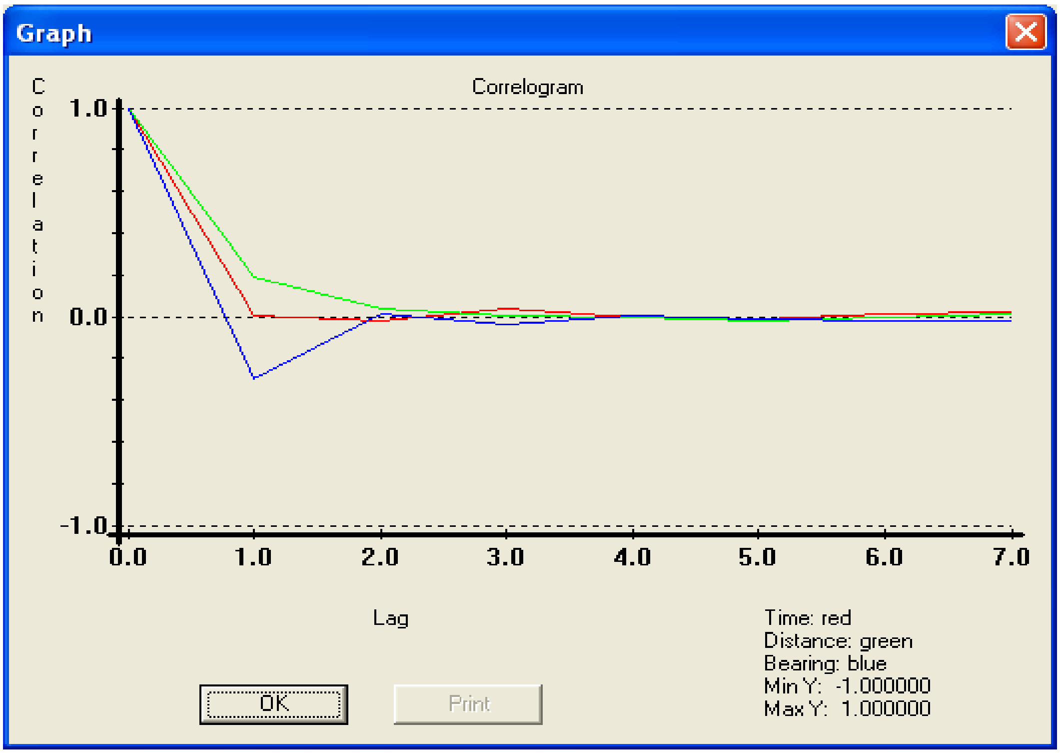

Figure 2. Correlated Walk Analysis – Correlogram

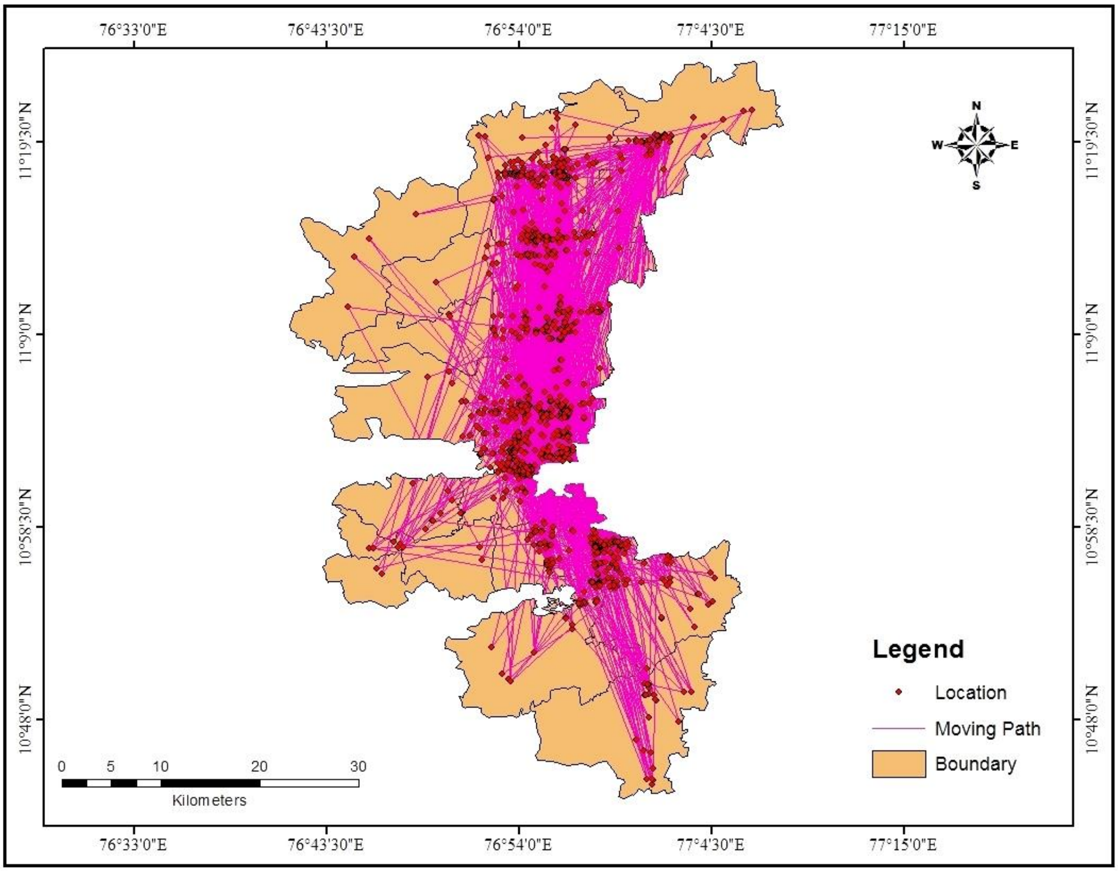

Figure 3. Moving path of peak crime incidences in space and time

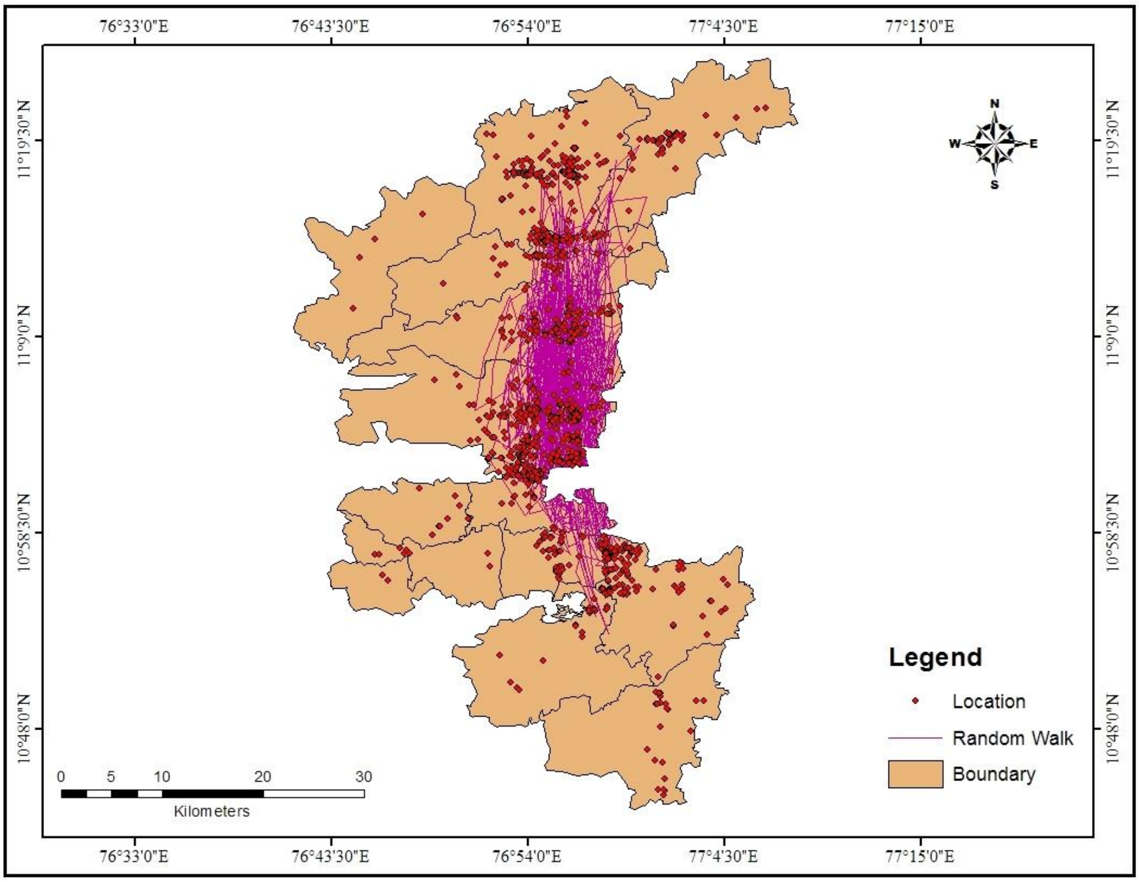

Figure 4. Random walk for crime incidences in space and time

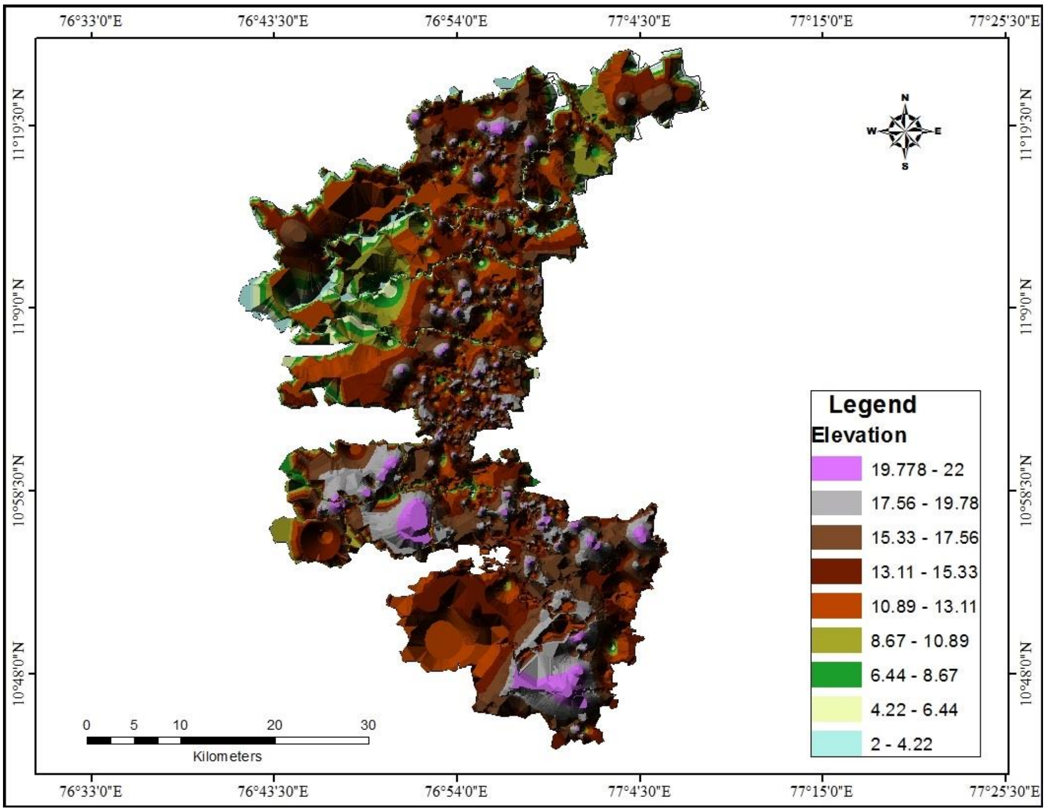

Figure 5. 3D Elevation map of Spatio-temporal analysis

Table 1. Logical Structure of Knox Index (Observed)

Distance/Time	Close in time	Not close in time	
Close in distance	O_1	O_2	S_1
S_3		S_4	
Not close in distance	O_3	O_4	S_2
	S_3	S_4	

Table 2. Logical Structure of Knox Index (Expected)

Distance/Time	Close in time	Not close in time
Close in distance	E_1	E_2
Not close in distance	E_3	E_4

Table 3. Observed Frequencies of Knox Index

Distance/Time	Close in time	Not close in time	
Close in distance	293118	225231	518349
Not close in distance	230573	187474	418047
	523691	412705	936396

Table 4. Expected Frequencies of Knox Index

Distance/Time	Close in time	Not close in time	
Close in distance	289893.06464	228455.93536	518349
Not close in distance	233797.93536	184249.06464	418047
	523691	412705	936396

Table 5. Knox Index for Crime Incidences

Year	Actual Chi-square	95% Simulation Chi-square	Approx. p level
2003	0.32314	10.91108	*ns
2004	45.00652	13.03143	*ns
2005	9.06724	5.76827	*ns
2006	6.51810	10.45437	*ns
Overall	182.33014	35.80534	*ns

* ns = non-significant

Table 6 Mantel index for incidences of crime from 2003-2006

Year	r	Simulation 2.5%	Simulation 97.5%	Approx p-level (**non-significant)
2003	0.00050	-0.03022	0.02738	**
2004	-0.00624	-0.02452	0.01680	**
2005	0.09727	-0.02863	0.02449	**
2006	0.01376	-0.01782	0.02117	**
Over all	0.01571	-0.01012	0.01080	**

Table 7. Regression Analysis for space- time analysis

Variable:	Time	Standard error or estimate		0.05428
Multiple R:	0.00871	Squared multiple R:		0.00008
	Coefficient	Std error	t	P (2 Tail)
Constant	0.008992	0.00149	6.04067	0.0000
Lagged variable	0.008706	0.02708	0.32155	0.74785

Table 8. Analysis of Variance

Source	Sum-of- squares	df	Mean square	F- ratio	P
Regression	0.00030	1	0.00030	0.10347	0.74776
Residual	4.02222	1366	0.00295	-	-
Total	4.02252	1367	-	-	-

Table 9. Analysis of predicted value

Variable	Predicted value	From event	Method	Lag
Time interval	0.00899	1369	Regression	1
Distance interval	0.14711	1369	Regression	1
Bearing interval	130.69419	1369	Regression	1

5. RESULTS AND DISCUSSION

Spatio-temporal methodology was applied to a hot incidence namely crime with relatively high incidence rates and a substantial spatial data structure. For this model, peak incidences in a time lag interval of 1 and the distance interval between the peaks. The map of smoothed trends in incidence rates shows a spatial pattern in time scale in relation to the baseline incidences. The spatio-temporal crime prediction model is adapted from Al-Madfai et al., (2006). Presently there are three important parameters considered to adapt the model. Scale of the study area and the number of crime data are considered in spatial analysis and, time period in temporal analysis of crime. The study area consists of fourteen police jurisdiction of the crime with nearly 1369 occurrences. The model is adapted considering the difference between scale and number of data. The number of clusters is generated higher than the crime prone area, considering the scale of the study area. Standard forecasting disaggregation weights are found by taking percentages of crime occurrences to the overall data per cluster.

Spatio-temporal analysis methods have applied that target to identify “unusual” clusters of events, or hotspots, in both spatial and temporal dimensions. We propose a space and time approach and it has been visualized through maps (Figure 3 and Figure 4). The first map shows the peak crime incidences in space and time, the second map shows the random walk for crime incidences and third map uses a real-world crime analysis data in 3dimensional view (3D) (Figure 5). The study shows that spatial distribution of rise in crime incidences is uneven and suggests a movement elevated risk of a crime to other areas in space and time. Clear evidence shows the stabilization of incidences in areas that have been previously at high risk. For crime to be properly managed, quality information about crime, the environment where it occurs, the socio-demographic data of the f crime victims and the perpetrators of crime are necessary for crime analysis.

Crime, socio-demographic and spatial data are needed in order to achieve effective, efficient and detailed crime analysis which is of great use to the decision makers. ArcGIS software created the data collected from suitable maps rural police jurisdiction. Crime prediction model is simple spatial disaggregation approach. The approach starts with forming appropriate clusters to control the model and predict the prospect values. Suitable clustering algorithm selected was STAC with distance application. The crime prediction model is based on year, day, time, place values, data is divided according to the intervals are mapped and analyzed with STAC algorithms. Forecasted values are evaluated in both the algorithms to compare the accuracy of the clusters. Also, prospect values are assigned to clusters to give information about the high probable crime areas and number of crimes.

Spatio-temporal analysis was created in crime prediction model. In earlier the analysis, clusters per week day and the number of incidents in these clusters are predicted. The number of incidents predicted indicates the level of sensitivity, higher the number of incidents predicted the more prone is the area to criminal activities. To prevent crime before occurrence is possible with identification of sensitive areas and reasons are explained by crime theories under environmental criminology.

Spatial temporal analysis revealed that the Daily Incident Reports (DIR) which is the major source of information for crime analysis only reflects serious crimes. Similarly, crimes that are not reported within 24 hours of occurrence are not included in the DIR. The study suggested that new way of recording particulars which will enable police officers to record location information using the rural boundary identification. In the new system, other socio-demographic data such as educational level of the victim which is not being recorded currently are included.

Mostly week day clusters are significant in terms of crime theories, as in each week day people have different daily activities. Each day has different cluster configuration as opportunities for some areas change according to the day of week. For example, many shopping areas are open at only one day of week which provides opportunity for offenders in that area. Shopping area covered by a cluster on that day, the criminal activities can be reduced by taking precautions in that area.

Police should utilize the model first by understanding the reason of clusters. Why the area covered by these clusters are attractive for offenders. Police needs background information about the area. The area is known and identified in terms of land use, configuration of buildings, important organizations; it is possible to detect opportunities for crime in the crime triangle. Further necessary action to take precautions against crime and crime situation is helpful and effective if the structure of crime is detected. Also, the methodology of this study can be used by police departments to be more informative about the future events.

To take precautions against crime the situational crime prevention which determine the more informative about the future events is helpful and effective. Also, the methodology of this study can be used by police departments. Some areas are exposed to crime quiet often. When the police understand the importance of crime analysis; hopefully, crime prevention in police station will be more effective. For this study becomes useful in detecting real crime patterns, forecast the future values, take appropriate prevention measures and allocate resources effectively.

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