

# GIS ANALYSIS OF SPATIALLY-REFERENCED AUTO VEHICLE THEFT CRIME IN COIMBATORE URBAN, INDIA: VISUALIZATION THROUGH KERNEL ESTIMATION

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## *Abstract*

Auto Vehicle Theft (AVT) is a serious problem with high social and economic costs, posing a much challenging duty for the Indian Police Force. The pattern of theft in urban areas tends to be unevenly distributed and follows a spatio-temporal distribution. The present study assesses and explains the spatio-temporal distribution of AVT in Coimbatore Urban of Tamil Nadu, India from 2003-2006.

Crime Pattern Analysis for AVT attempts to quantify the spatio-temporal distribution of crime. Through this exploratory data analysis, hotspots based on point pattern analysis through Kernel Density Estimation were identified. The changes in spatial distribution of AVT during the month of the year and day of the week were mapped. An attempt was made to investigate the relationship between the place of theft and recovery of motor vehicles within the study area.

The results of the study clearly depict the spatial density of AVT with temporal variations in the urban regions showing concentrated hotspots. The present study provides a significant insight to the approach of Crime Pattern Analysis, which can be employed for effective Offence determination.

**Keywords.:** AVT, KDE, Spatio-temporal, Crime pattern analysis.

## **1.0 INTRODUCTION**

Crime is not spread evenly across maps. It clumps in some areas and is absent in others. Using started choropleth mapping methods, levels of crime intensity can be displayed to show geographical variation. The spatially discontinuous choropleth map is a poor representation of the underlying continuous distribution of population density.

Members of the cartographic school included Guerry, (1833) analyzed crime patterns in frame and status. Later, Mayhew, (1862) examined variation in crime by population density, concluding that crime is most prevalent in industrial and urban areas.

Geography that “everything is related to everything else, but near things are more related than distant things” (Tobler, 1979). The Brantinghams’ identify four dimensions of environmental criminology: legal, offender, target or victim, and place or spatial dimension; and Bottoms and Wiles (1997:305) defined it later as: “...the study of crime, criminality and victimization as they relate, first, to particular places, and secondly, to the way that individuals and organizations shape their activities spatially, and in so doing are in turn influenced by place-based or spatial factors.”

Point maps are the simplest way to visualize point data, but when large numbers of points occur at the same location it is difficult to differentiate between areas with high densities of points. To identify risk areas spatially referenced point data can be analyzed through GIS / point pattern analysis.

Spatial analyze of Point Pattern involves the ability to describe patterns of locations of point events and test whether there is a significant occurrence of clustering of points in a particular area. In general, Point Pattern Analysis can be used to describe any type of incident data (Chakravorty, 1995).

According to Sherman, (1995) stated that hot spots “as small places in which the occurrence of crime is so frequent that it is highly predictable, at least over a one-year period.” Areas of concentrated crime are often referred to as hot spots. Researchers and police use the term in many different ways. Some refer to hot spot addresses (Eck and Weisburd, 1995; Sherman, Gartin, and Buerger, 1989), others refer to hot spot blocks (Taylor, Gottfredson and Brower, 1984; Weisburd and Green, 1994), and others examine clusters of blocks (Block and Block, 1995).

Spatial point pattern analysis began its emergence in the late 1950s and 1960s but, it had been neglected in geography because of two reasons at that time:

- (i) More significant is that the null hypotheses with which most of the early methods were concerned was rarely of real practical value and
- (ii) Lack of availability of good software existing programs generated purely textual output of statistical summaries and little or nothing in the way of maps or other graphical displays.

However, in the intervening year, point pattern analysis was introduced in many fields such as archaeology, criminology, astronomy including epidemiology to understand the sudden breakout of diseases and to identify if there was a pattern. Later on, this method grew importance in the field of health sciences to identify disease patterns and to detect areas of high risk to mainly allocate available resources.

Bithell, (1990) used point pattern analysis to surface the cases of Leukemia intensity in children of Cumbria and to identify clustered peaks in the surface map. The author adopted kernel estimation with a choice of bandwidth to explore the hotspots of Leukemia in the region. Computer mapping is emerging as an important tool for criminal justice practitioners (Block *et al.*, 1995; Maltz, Gordon, and Friedman 1991). (Sherman, Gartin and Buerger 1989; Block 1995; Rengert, 1995a) stated that the hot spots of crime has become as an increasing focus on research and also as an area in which computer generated maps are essential for the visual presentation of these spots. Similarities and overlaps exist between GIS and point pattern analysis, especially in that they are both concerned with the analysis of spatial data. The most significant difference is that point pattern analysis has much firmer statistical base which provides powerful hypothesis – testing capability. Hence, there is a need to integrate GIS and point pattern analysis.

To concentrate of point patterns; probably driven by the need to define hotspots in disease outbreaks and crime. When locations are imprecise the analysis is more complex (Jacquez, 1996). The Hot Spot Detective developed by Jerry Ratcliffe, (2006) uses the raster grid scan approach to calculate a regular grid using the kernel estimation approach of Bailey and Gatrell *et al.*, (1996) that was developed

specifically to address the point analysis hotspot problem in epidemiology. The advantage of the kernel method is that it generates an isodensity surface using the technique Ratcliffe *et al.*, (1999) where a count is made on a regular grid of all points lying within a given search radius.

Clustered point patterns can be visualized spatially as local concentrations of events in close proximity to one another with each cluster separated by intervening spaces characterized by empty, less dense or apparently random patterns of point events. However, assured classes of point event patterns have a significant percentage of their data have a tendency towards exact spatial uniformity. Type of examples would include: crimes recorded against a property address (e.g. Auto vehicle theft, robbery, pocket picking). The focus of analysis of such data sets is in defining 'hot spots' (e.g. crime) where spatial clustering exists, but the occurrence of this spatial point events existing approaches to cluster detection.

The methods for the analysis of spatial point pattern could be classified into two broad types (Dacey, 1962; King, 1962; Rogers, 1965; Trenhaile, 1971; Haggett *et al.*, 1977) based on the following two data sets.

- (i) Distance based technique: Using the information on the spacing of the points to characteristic pattern (typically, mean distance to the nearest neighboring point).
- (ii) Area based technique: Relying on various characteristics of the frequency distribution of the observed numbers of points in regularly defined sub-regions of the quadrates known as study area.

The patterns detected are usually broadly classified as random, uniform or clustered. Where a point pattern exhibits spatial uniformity, a space-filling mutual exclusion process can be hypothesized. Clustered patterns, however, have generally raised the strongest interest and hypotheses for underlying processes.

An important activity in the analysis of crime data is the detection of hotspots or clusters of criminal activity. Hotspot detection may be important at several different scales of analysis. At the level of the police beat, patrol officers wish to know where activity has recently occurred in their area. At larger geographical scales, crime analysts look for patterns to decide how to allocate and deploy resources effectively.

## 2.0 SPATIAL POINT PATTERN MODELING

*Complete spatial randomness* is the simplest theoretical model for a spatial point pattern, in which the events are distributed independently with a uniform probability distribution over the region  $R$ . Observed events are displayed in a systematic spatial pattern or departure from randomness either in the direction of *clustering* or *regularity*. From a statistical point of view, an observed spatial point pattern can be thought of as the outcome (a *realization*) of a spatial stochastic process. Mathematically, we may express this in different ways, but one useful possibility is in terms of the number of events occurring in arbitrary sub-regions or areas  $A$ , and of the whole study region,  $R$ . Accordingly, the process is represented by a set of random variables:

$$Y(A), A \in R, \dots\dots\dots(1)$$

where,

$Y(A)$  is the number of events occurring in the area  $A$ .

Behavior of a general spatial stochastic process may be characterized in terms of its so-called *first-order* and *second-order* properties. The first-order properties describe the way in which the expected value (mean or average) of the process varies across space, while second-order properties describe the covariance (or correlation) between values of the process at different regions in space. First-order properties are described in terms of the *intensity*,  $\lambda(s)$ , of the process, which is the mean number of events per unit area at the point. This is defined as the mathematical limit:

$$\lambda_\tau(s) = \lim_{ds \rightarrow 0} \left\{ \frac{E(Y(ds))}{ds} \right\} \dots\dots\dots(2)$$

where  $ds$  is a small region around the points,  $E$  is the expectation operation and  $ds$  is the area of this region.  $Y(ds)$  represents the number of events in this small region.

The second-order proportion describes the spatial dependence where the relationship between numbers of events is explained in pairs of sub-regions within  $R$ . Thus the second order intensity is described as:

$$\lambda(s_i, s_j) = \lim_{ds_i, ds_j \rightarrow 0} \left\{ \frac{E(Y(ds_i) Y(ds_j))}{ds_i ds_j} \right\} \dots\dots\dots(3)$$

where  $ds$  is a small region around the point  $s$ ,  $E()$  is the expectation operator and  $ds$  is the area of this region.  $Y(ds)$  refers to the number of events in this small region.

The second-order properties, or spatial dependence, of a spatial point process involve the relationship between numbers of events in pairs of sub regions within  $R$ . The *second-order intensity* of the process:

$$\gamma(s_i, s_j) = \gamma(s_i, s_j) = \gamma(d) \dots\dots\dots(4)$$

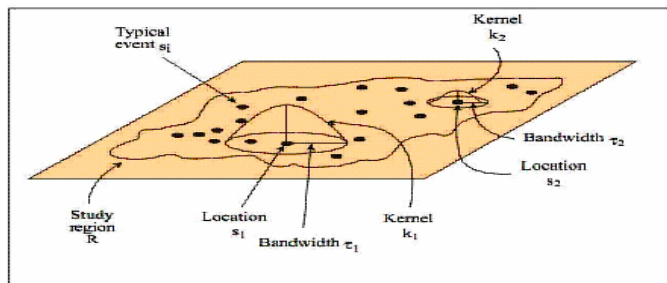
It implies that the second-order intensity depends only on the vector difference,  $d$  (direction and distance), between  $s_i$  and  $s_j$  and not on their absolute locations. The process is further said to be *isotropic* if such dependence is a function only of the length,  $d$ , of this vector  $d$  and not its orientation. Henceforth, we use the term *stationary* without qualification to mean stationary and isotropic.

### 3.0 KERNEL DENSITY ESTIMATION

Kernel density estimation is an interpolation technique that generalizes individual point locations or events,  $s_i$ , to an entire area and provides density estimates,  $\lambda(s)$ , at any location within the study region  $R$ . From a visual point of view it can be thought of a three-dimensional sliding kernel function  $K(\bullet)$  that 'visits' every location  $s$  (Figure 1).

Distances to each observed event  $s_i$  that lies within a specified distance  $b$ , referred to as the bandwidth, are measured and contribute to the intensity estimate at  $s$  according to how close they are to  $s$  (Bailey, 1996). This produces a more spatially smooth estimate of variations in  $\lambda(s)$  than could be attained by using a fixed grid of quadrates. Formally, if  $s$  represents a vector location anywhere in  $R$  and  $S_1, \dots, S_n$  are the vector locations of the  $n$  observed events, then the intensity  $\lambda(s)$ , at  $s$  is estimated as follows (Burt and Barber, 1996).

Figure.1 Kernel estimation of point pattern (Fischer, 2001)



$$\hat{\lambda}(s) = \frac{1}{n\tau^2} \sum_{i=1}^n K\left(\frac{s-s_i}{\tau}\right) \dots\dots\dots(5)$$

There are a number of different kernel functions. However, since the result of an analysis is not strongly influenced by the chosen function as long as the function is symmetric (Silverman, 1978; Burt and

Barber, 1996) there are no binding rules concerning the choice of an appropriate function. The most common kernel function is the normal distribution function

$$K\left(\frac{d_i}{b}\right) = \frac{1}{2\pi} \exp\left(-\frac{1}{2}\left(\frac{d_i}{b}\right)^2\right) \quad \text{----- (6)}$$

With

$$u = \left(\frac{d_i - s_i}{b}\right) \quad \text{----- (7)}$$

Based on this function the density estimate is expressed as (Burt and Barber, 1996)

$$\lambda(s) = \frac{1}{2\pi} \sum_{i=1}^n K\left(\frac{d_i}{b}\right) \quad \text{----- (8)}$$

Where,  $d_i$  is the distance between the point  $s$  and the observed event location  $s_i$ .

As the bandwidth  $b$  is the standard deviation of the normal distribution, this function extends to infinity in all directions, i.e., it will be applied to each point in the region (Leitner, 2001). The quadratic kernel function on the other hand, has a circumscribed radius  $b$ , which is also the bandwidth. The quadratic kernel function is therefore applied to a limited area around each event and has the following functional form (Bailey, 1995).

$$K(u) = \begin{cases} \frac{3}{4}(1 - u^2)^2 & \text{for } |u| \leq 1 \\ 0 & \text{otherwise} \end{cases} \quad \text{----- (9)}$$

The intensity at  $s$  is estimated as

$$\lambda^q(s) = (n + \alpha)^{-\alpha} = \left(1 - \frac{d_i^2}{b^2}\right) \left[1 - \frac{d_i^2}{b^2}\right] \quad \text{----- (10)}$$

Since  $d_i \leq b$ , the summation is only over values of  $d_i$ , which do not exceed  $b$ . The region of influence within which the observed events contribute to  $\lambda(s)$  therefore equals a circle of radius  $b$  centered on  $s$ . In  $s$  the weight is  $3/\pi b^2$  and drops smoothly to a value of zero at distance  $b$  (Bailey and Gatrell, 1995). This function can be extended by a weighting variable ( $W_i$ ) as is shown in (Levine, 2004):

$$\lambda^q(s) = \sum_{i=1}^n \frac{W_i}{\pi} \left[ \left(1 - \frac{d_i^2}{b^2}\right) \right] \quad \text{----- (11)}$$

More important than the kernel function is the choice of an appropriate bandwidth  $b$  (Silverman, 1986), which has considerable influence on the estimated distribution. The effect of increasing the bandwidth  $b$  is to stretch the region around  $s$  within which observed events influence the intensity estimate at  $s$ . For very large  $b$ ,  $\lambda(s)$  will appear flat and local features will be obscured. If  $b$  is small, then  $\lambda(s)$  tends to a collection of spikes centered on  $s_i$  (Fischer, 2001).

There are several methods which attempt to optimize the value of  $b$  given the observed pattern of event locations. Basically, the bandwidth can either be fixed (fixed kernel estimation) or adaptive (adaptive kernel estimation). In adaptive smoothing sub-areas in which events are more densely packed than in others are visited by a kernel whose bandwidth is smaller than elsewhere in order to avoid smoothing out too much detail. In the fixed choice, the bandwidth always stays the same. When using a fixed interval, the appropriate choice of the smoothing parameter will be influenced by the purpose for which the density estimate is to be used. Hereby, several different plots of the data, all smoothed by different amounts, are examined and the bandwidth that seems most in accordance with one's prior ideas about the density is chosen. Silverman (1986) calls this approach "smoothing by eye" as opposed to automatic methods.

Within the scope of this study it seems sufficient to rely on a subjective choice of the bandwidth since retail outlets have a certain catchments area that has to be allowed for when analyzing market concentration and market dominance. Thus, the choice of the bandwidth has to find a compromise between the requirements of a reasonable density estimate and an area that is not too wide. For every analysis within this study a quadratic kernel functions and a fixed bandwidth of 1500 meters is used.

If the Kernel Density Estimation (KDE) is applied to one variable, this is referred to as a single density estimate. If it is applied to two variables, it is called a dual density estimate. In the latter case, a kernel density is estimated for each variable individually and then the two density estimates are related with each other through simple algebraic operations such as the sum, the difference, the quotient and the like. The most commonly used operation in this realm is the quotient. In the present study, however, the absolute difference in densities is used to visualize spatio-temporal changes in the study region.

#### 4.0 DENSITY CALCULATION

The density estimate for each cell can be calculated using any one of the three ways

- Absolute densities: This is the number of points per grid cell and is scaled so that the sum of all grid cells equals the sample size. This is the default.
- Relative densities: For each grid cell, this is the absolute density divided by the grid cell area and is expressed in the output units (e.g., points per square km).
- Probabilities: This is the proportion of all incidents that occur in the grid cell. The sum of all grid cells equals a probability of 1.

We have used probability method for the present study to calculate the kernel estimate of the incidences in the given area. A consistent approach to cluster detection and visualization of the hotspots is performed through the combined use of point pattern analysis using CrimeStat III and ArcGIS 9.1.

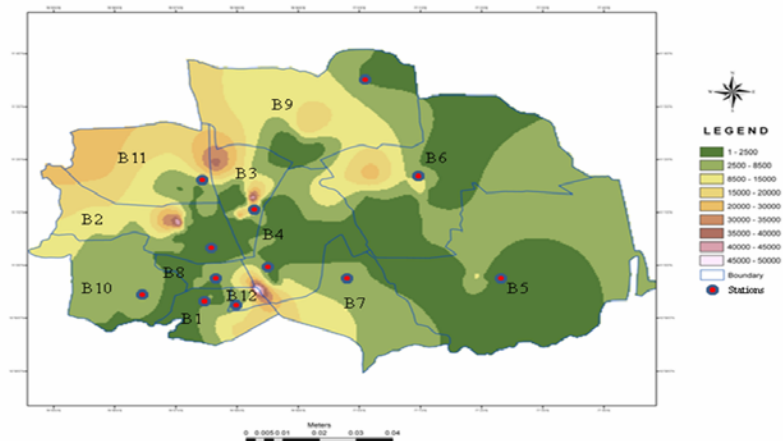
#### 5.0 DATA USED

The recorded geo-coded data of Auto vehicle Crime incidences from the Coimbatore urban police limits were used to estimate the hot spot of Crime incidences for the period from January 2003 to December 2006. The study area covered for hot spot analysis includes all police stations under Coimbatore city limits. CrimeStat III was used for the hot spot analysis. Since, CrimeStat does not have its own visualization capability; it relies on external GIS software. For our study we used ArcGIS 9.1 to implement visualization of the results and obtained a smoothed map.

#### 6.0 RESULTS

Smoothing of the entire area is performed using kernel estimation as an interpolator. A ratio of the density estimate of crime incidences to the density estimate of total population was obtained and mapped through interpolation method. The dual kernel technique involves using the density of the individual cases over the population at risk and the ratio is applied to obtain a spatial smoothed map of risk. The estimation was made using a grid cell size of 250 meters and a fixed bandwidth of 1500 meters (Ali *et al.*, 2003). The

Map 1 Smoothed map of Kernel estimation using Point Pattern Analysis of crime incidences in Coimbatore Urban, INDIA



smoothed surface is created based on the sum of these individual kernels.

From the resultant Map 1, central part it is clearly observed that risk areas are clustered in the old Coimbatore city area police stations, which includes the Race course (B-4) police limit, R.S Puram (B-2), Kattur (B-3) and SB colony (B-11). The intensity of distribution of crimes appears to vary in the study area and it exhibits a gradual pattern in Ukkadam (B-12). The less intensity area depicts in the Map 5.2.2 is Peelamedu (B-6) and Saravanampatti (B-9) police limits. A unique observation from the map is that the clustered crimes are not specifically within a police station limit, for example, the cluster very near to Ukkadam (B-12) station is a junction of Big Bazaar St (B-1) and VH RD (B-8). Similarly the cluster on Kattur (B-3) and SB Colony (B-11) is a combination of B-3 and B-11. The result clearly reveals that the maximum clustered crime was occurred in thickly populated areas. In addition it is also observed that the central bus stand and Ukkadam bus stand are the places where the mobility of population almost rounds the clock. Therefore the Kernel density estimation is a useful method for hot spot analysis which correlates with the mobility of population rather than the permanent residents. Kernel density is applied to identify the hotspots and it is not an interpolation technique, but more precisely the estimation of a probability surface. To test the statistical significance Nearest Neighbor Index and Ripley's K is applied to the data.

### 6.1 NEAREST NEIGHBOR ANALYSIS

This method measures the distance from one point to the nearest neighbor point. In general there are three different functions that users are able to employ in Nearest Neighbor Analyses. Clark and Evans (1954) developed nearest neighbor analysis to analyze the spatial distribution of plant species. They developed a method for comparing the observed average distance between points and their nearest neighbors with the distance that would be expected between nearest neighbors in a random pattern. The nearest neighbor statistic, **R**, is defined as the ratio between the observed and expected value

$$R = \frac{\bar{d}_n}{\bar{d}_r} \quad \text{----- (12)}$$

Where  $\bar{d}_n$  is the mean of the distances of points from their nearest neighbors, and  $\lambda$  is the number of points per unit area. **R** varies from 0 (a value obtained when all points are in one location, and the distance from each point to its nearest neighbor is zero), and a theoretical maximum of about 2.14, for a perfectly uniform or systematic pattern of points spread out on an infinitely large two-dimensional plane. A value of R=1 indicates a random pattern, since the observed mean distance between neighbors is equal to that expected in a random pattern. To test the null hypothesis of no deviation from randomness, a z-test is employed:

$$z = 3.826(R_o - R_e) (\sqrt{\lambda n}), \quad \text{----- (13)}$$

where, n is the number of points. The quantity z has a normal distribution with mean 0 and variance 1, and hence tables of the standard normal distribution may be used to assess significance. A value of z > 1.96 implies that the pattern has significant uniformity, and a value of z < -1.96 implies that there is a significant tendency toward clustering. The measured distance through the NNI as presented in Table 1 it indicates that the crime data exhibits a clustered pattern, with Z test statistics of -4.17 significant at p=0.0001 for both one-tailed and two tailed tests. NNI value is 0.70 which lies between 0 and 1, more or less as a centroid value indicating partial clusters and dispersion. The observed clusters had high peaked values ranging from 0.5 to 5.

**Table 1 Table showing the NNA (nearest neighbor analysis) of Crime incidences in the Coimbatore city of India using CrimeStat**

<b>Sample size</b>	<b>52</b>
Mean nearest neighbor distance	482.18 m
Standard dev of nearest Neighbor Distance	690.45 m
Minimum Distance	11.11 m
Maximum Distance	11646.08 m
Nearest neighbor index	0.70
Test statistic	-4.17
p-value (one tail, two tail)	0.0001

## 6.2 RIPLEY'S K FUNCTION

Ripley's 'K' statistic compares the number of points within any distance to an expected number for a spatially random distribution. The traditional K-function evaluating the clustering of points on a plane is Ripley's K function (Ripley, 1976; 1981; Bailey and Gatrell, 1995; Diggle, 2003).

$$K(d) = \lambda^{-1} \times E(d, \zeta, \square) \quad \text{----- (14)}$$

$$K(d) = \lambda^{-1} \times n^{-1} \sum_{i=1}^n P_i(d) \quad \text{----- (15)}$$

where  $d$  indicates the distance for which the  $K$  is calculated,  $\lambda$  is an unbiased estimation of the distribution density of the points in  $\zeta$ ,  $E$  represents the expected number of points within distance  $d$  to a random point in set  $\zeta$  over plane,  $P_i(d)$  denotes the number of points observed within distance  $d$  of point  $i$ , and  $n$  is the total number of points in  $\zeta$ . By increasing  $d$  from small to large, typically with 50–100 small increments to cover the extent of point set  $\zeta$  on plane, a series of  $K(d)$  can be obtained and plotted against  $d$ . By comparing the curve of  $K(d)$ , with that of  $K(d)$ , one can tell if the observation set,  $\zeta$ , is clustered, randomly distributed, or dispersed at certain distances. The increment of  $d$  depends, among other things, on the size of the study area and the number of points in  $\zeta$  (Levine, 2004).

**Figure 2 Ripley's K function**

This hypothesis was applied for the crime data of the Coimbatore city using CrimeStat III as mentioned earlier. The calculated values of K function are stored and a graph was prepared and presented as *Figure 2* from the graph it is observed that the K values are away from the boundary (envelope) which clearly indicates that clustering of the crime incidences was observed. The Ripley's K function confirms the earlier NNI as presented in *Table 1*. The result of nearest neighbor analysis indicates that the crime data exhibits a clustered pattern, with Z test statistics of -4.17 significant at  $p=0.0001$  for both one-tailed and two-tailed tests. NNI value is 0.70 which is closer to 0 than 1 indicates a clustered pattern.



### 6.3 METHODS OF AGGREGATED DATA

Summarizing a group of individual data points into a single value ‘s’ the process of aggregation and autocorrelation statistics is applied for the aggregated data to facilitate in the degree of spacing similarity observed among neighboring values over the study area of the Coimbatore city.

There are several methods available for autocorrelation statistics. For eg. Time series autocorrelation is the popular test statistics for Residual Variance (RV), Akiaike Information Criteria (AIC), Bayesian Information Criteria (BAC), and Posterior Probability Criteria (PP). For aggregated data we cannot used the above statistics but alternatively we can use Moran’s I and Geary’s C for the present study.

#### 6.3.1 MORAN’S I

The analysts have access only to crime point data that are aggregate counts (representing the number of crime events within a certain geographic area e.g. for census blocks) an appropriate method to apply to test for clustering is the spatial technique. Moran’s I statistic works by comparing the value at all other locations (Levine, 2004; Bailey and Gatrell, 1995; Ansellion, 1992). In this analysis an intensity required value for the point, this often represented as the centroid of the geographic boundary area. Point is then assigned an intensity value, crime applications most often in count of crimes within that geographic area. Moran’s I result varies between -1.0 and +1.0. Where points that are close together have similar values, the Moran’s I result is high.

The point locations are not available, and data are given for areas only. Moran’s I statistic (1954) is one of the classic ways of measuring the degree of pattern (or, spatial autocorrelation) in a real data. Moran’s I is calculated as follows:

$$I = \frac{n \sum_i \sum_j W_{ij} (y_i - \bar{y})(y_j - \bar{y})}{n \sum_i \sum_j W_{ij} \sum_i (y_i - \bar{y})^2} \quad (16)$$

Where there are *n* regions and *w<sub>ij</sub>* is a measure of the spatial proximity between regions *i* and *j*. It is interpreted a correlation coefficient. Values near +1 indicate a strong spatial pattern Values near -1 indicate strong negative spatial autocorrelation; high values tend to be located near low values. Finally, values near 0 indicate an absence of spatial pattern. In the present study, the value for Moron’s I is observed in the *Table 2* and presented as a graph in the *Figure 3*.

*Table 2 The results for spatial autocorrelation for point data*

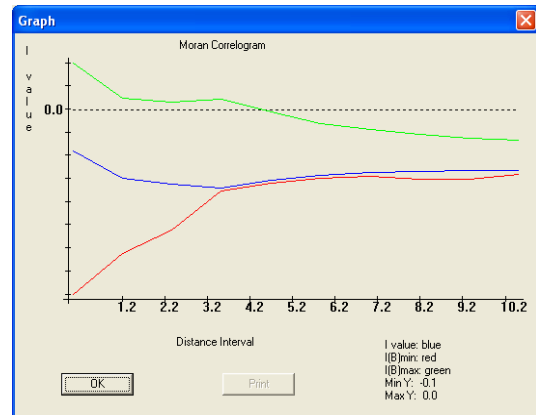
S.No	Spatial Autocorrelation	Value
1	Moran’s I	-0.023
2	Geary’s C	1.17

The above mentioned *Table 2* shows the value Moran's *I* is observed to be -0.023 which is a negative value. Therefore it is considered that there is a partial negative spatial autocorrelation exists in the point data.

### 6.3.2 GEARY'S C

Moran's *I* consider un-similarity between neighboring regions where as Geary's *C* considers similarity between pairs of regions. Geary's *C* or Geary's contiguity ratio is another weighted estimate of spatial auto correlation.

**Figure 3 The Graph of Moran's I**



$$C = \frac{(N-1)\sum_i\sum_j w_{ij} (X_i - X_j)^2}{2W \sum_i (X_i - \bar{X})^2} \dots\dots\dots (17)$$

Where *N* is the number of spatial units indexed by *i* and *j*; *X* is the variable of interest;  $\bar{X}$  is the mean of *X*; *w<sub>ij</sub>* is a matrix of spatial weights; *W* is the sum of all *w<sub>ij</sub>*.

Geary's *C* ranges from zero to two, with zero indicating perfect positive spatial autocorrelation and two indicating perfect negative spatial autocorrelation for any pair of regions. In our study the value is 1.17 which is oscillating between 0 and 1 indicates partial positive spatial autocorrelation as confirmed by Moran's *I* (*Table 3*).

**Table 3 The Geary's C of Crime incidences in the Coimbatore City of India using CrimeStat**

<b>Sample size</b>	<b>52</b>
Geary's 'C'	1.17
Spatially random (expected) "C"	1.000000
Standard deviation of "C"	0.036250
Normality significance (Z)	4.725535
p-value (one tail, two tail)	0.0001

Geary's *C* ranges from zero to two, with zero indicating perfect positive spatial autocorrelation and two indicating perfect negative spatial autocorrelation for any pair of regions. The result of Geary's *C* analysis indicates that the crime data exhibits a clustered pattern, with Z test statistics of 4.725535

significant at  $p = 0.0001$  for both one-tailed and two-tailed tests. Geary's C value is 1.171301 which is closer to 0 than 1 indicates a clustered pattern.

## 6.4 CONCLUSION

From the above results, we have developed a spatial surface of Coimbatore city police jurisdictions that interpretation of crime data which requires additional knowledge and further analytical approach for cluster detection and visualization of hot spots. Point pattern analysis is performed (stochastic statistical method) to group variables or observations into strongly interacted subgroups. Kernel density estimation is applied to transform the point events into a more or less smoothed continuous surface. With an underlying population at risk, kernel density estimation represents the relative risk of crime occurrences. This approach attempts to estimate even low event frequencies across the study area based on the point patterns.

The recorded crime data exhibits a clustered pattern which is confirmed by NNI and Ripley's K test. The degree of similarity observed among neighboring values indicates that there exists partial positive auto correlation in the point data. Though, time factor is an invisible component of point pattern analysis the relevance of temporal data with that of spatial data gives the trend of crime patterns.

Investigative time and spatial variations of crime cases would be necessary in forming crime prevention and control programmes and also consign strategic plans into actions. Here, the spatial point pattern method was adopted for a large area and for spatially distributed point locations. However, this method can be suggested for micro level studies which require elaborate data to identify intrinsic pattern of crime distribution. The next section details spatial trend of the crime at different time scales of the study period.

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