REVIEW OF RESEARCH
IMPACT FACTOR : 5.7631(UIF) UGC APPROVED JOURNAL NO. 48514 ISSN: 2249-894X

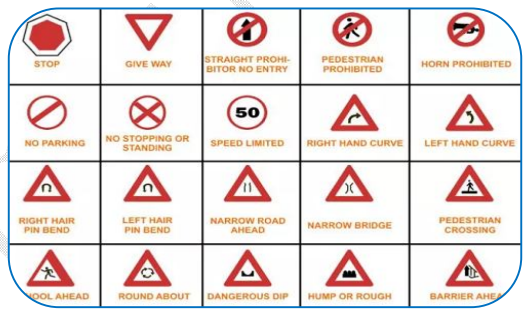
VOLUME - 8 | ISSUE - 6 | MARCH - 2019

SPATIAL ANALYSIS OF ROAD SAFETY MEASUREMENTS: A MODEL STUDY FROM ANDHRA PRADESH

Charankumar Ganteda[1] and Shobhalatha G.[2]
[1]Research scholar, Department of Mathematics, Srikrishnadevaraya University, Anantapur, (A.P.), India.
[2]Professor, Department of Mathematics, Srikrishnadevaraya University, Anantapur, (A.P.), India.

ABSTRACT :

Spatial investigation assumes a key role in examining the information identified with the graph theory in various fields with spatial contexts Spatial Characterizing the spatial region of the substances being contemplated is the crucial issue in the spatial graph theory. In the present study we made an attempt to analyze the spatial data related to the road safety by identifying the several discrepancies in various locations of selected area. We observed that the spatial dependencies and the relation between variables by using Spatial autocorrelation. From the analysis, we clearly noted that the discrepancy wise relation between the entities and its impact on road safety measurements.



KEYWORDS : *Spatial entities, distance matrix, spatial autocorrelation, spatial dependencies.*

1. INTRODUCTION:

Spatial investigation or spatial insights consolidates various frameworks and concentrate the substances like geographical properties. Spatial examination has grouping of systems using different procedures associated various fields most noticeably in the examination of geographic data. The essential issue in the spatial examination is portraying the spatial zone of the components being considered. The study of disease transmission contributed with early work mapping on flare-up cholera. The spread of infection and with area reads for social insurance conveyance. John snow (1854) first uses of map based spatial analysis. Moran (1950) tried spatial reliance dependent on the spatial autoregressive model. Ore, O (1961) perceived an issue with respect to the following of charts. Kobayashi (1997) provides generalization on a spatial graph theory. Gyananath et al. (2001) assessed environmental parameter on ground water quality. Structural landscape connectivity developed by using algorithms of spatial graph (Fall et al 2007 and Dale and Fortin, 2010). Spatial regression should consists of three main categories depending on how spatial influences modelled (Dormann et al., 2007 and Beale et al 2010): i) space incorporated in covariate predictors ii) space involved in error term iii) spatial impacts in the response or explanatory variables are replaced by changing the original data. Dale and Fortin (2010) described the transition from graphs to spatial graphs. Grifth (2011) studied spatial autocorrelation and filtering through scientific visualization. Prudhomme et al (2013) identified spatial autocorrelation in take-up of antenatal thought and relationship to nuclear family unit and town level elements: results from a community based survey of pregnant women in six districts of western Kenya. Fanc and Myint (2014) compared spatial autocorrelation and landscape metrics are helpful to measure urban landscape fragmentation land scape and urban planning. Russell R. Barton (2015) developed simulation Metamodelling. Russell R. Barton (2015) developed simulation Metamodelling. Saurav Kaushik (2016) studied clustering and its different methods. Ali Moradi et al (2016) did spatial examination to recognize high hazard zones for traffic crashes. Erica Flapan et al (2016) developed spatial graphs to intrinsic knotting and linking results. Erica Flapan et al (2017) developed spatial graphs to intrinsic knotting and linking results. Kamaldeep singh et al (2017) studied modeling of urban road traffic using spatial graph theory. Mark altaweel (2017) provided GIS and spatial autocorrelation, analysis. Praveen and Rama (2017) studied A K- Means Clustering algorithm on Numeric data. Charankumar and Shobhalatha (2019) analyzed the water quality analysis by using spatial graph theory and Metamodelling. Charankumar et al (2019) measured spatial dependencies of several spatial objects with respect to low safety. Charankumar and Shobhalatha (2019) studied shortest path for Graph clustering in Network analysis. A matrix is a convenient and useful way of representing a graph.

In the present study, we made an attempt to identify the discrepancies occurred in various locations in relation with the spatial objects and its dependencies by using Moran's I index.

2. METHODOLOGY:

First we will review the existing literature about spatial graphs and how it shows the similarities concerning the particular areas can be studied.

2.1 Data used

To carry out this research work the researcher has taken data through primary and secondary sources. In the selected area we collected 300 samples among them we observed that the discrepancies due to Bridge, Gap in Median, industry, Toll plaza, Truck/bus layby.

2.2 Spatial graph theory:

Spatial graph provides a graph in the 3-dimensional Euclidean space R^3 or the 3-sphere. For a graph ▯ we take an embedding f: ▯ $\rightarrow R^3$ then the image of spatial graph of G can be represented by $\bar{G}$=f(▯). It is a generalization of Knot and link. Dale and Fortin (2010) described the transition from graphs to spatial graphs.

A distance between two vertices U and V of a associated or connected graph is the length of the shortest path connecting them. For an associated graph G,

E(V)=Maximum dist (V,x) the eccentricity of V in G.

D(G)= Maximum E(V) is the diameter of a G

R(G)=Minimum E(V) the radius of G.

2.3 Spatial dependency using Moran's I index:

Moran's I is a spatial statistic which measure the spatial autocorrelation. It measures how much close objects are in examination with other close objects. It can be referred as positive, negative and no spatial relation between the entities. Positive correlation indicates that the similar values group together in a map. Negative spatial correlation represents the dissimilar values group together in a map. In general, we assume important property that the observation being independent. If autocorrelation exists in the data, then the property will be violated. Spatial autocorrelation gives us an idea about the clustering or dispersion in a map. Generally, spatial autocorrelation requires observations and locations.

Patrick Alfred pierce Moran has developed formulae to find the spatial autocorrelation is given by

$$I = \frac{N}{\sum\sum w_{ij}} \frac{\sum_i \sum_j w_{ij}(y_i - \bar{y})(y_j - \bar{y})}{\sum(y_i - \bar{y})^2} \qquad (1)$$

Where N gives the number of objects or spatial units indexed by i and j y is the variable of interest, $\bar{y}$ is the mean of y, w_{ij} is a matrix of spatial weights with zero's on the diagonal (ie., w_{ii}=0) and w is the sum of all w_{ij}.

Similarity = $(y_i - \bar{y})(y_j - \bar{y})$, similarities between units is calculated as the product of the difference between y_i and y_j with the overall mean.

1. I=-1 represents perfect clustering of dissimilar values or perfect dispersion.
2. I=+1 represents perfect clustering of similar values or perfect precision
3. If I=0 no auto correlation or perfect randomness.

By using spatial autocorrelation, we set null hypothesis that the observed spatial pattern is similarly likely as some other spatial pattern or the qualities at one area do not rely upon qualities at other neighboring areas.

3. RESULT AND CONCLUSIONS:

Following the above existing literature on spatial graph theory, we made an attempt to grouping the entire data into based on the discrepancies occurred at various places among the selected samples. Spatial graph theory will be helpful to study the spatial dependencies by using Moran's I index which is given in section (1). Table (1) provides the % contribution of each discrepancy. Table (2) gives the Moran's I index values for different groups, based on table (2) we draw the conclusions. First we determine the distance matrix between each cluster Centroids are calculating based on the Longitude and Latitude of the spatial areas selected in our study region. After calculating distance matrix, we obtain the spatial dependencies among the groups based on the discrepancy raised in the data.

Table: 1 Frequency of Discrepancies in different locations in the selected area

S.NO	DISCREPANCIES	NO OF POINTS	Probability
1	Bridges	6	0.14
2	Gap in medians	20	0.47
3	Industry/Institue/Intersections	7	0.15
4	bus or truck bays	5	0.12
5	Piligrimages/shandy/Tollplaza	5	0.12

Table: 2

Discrepancies	Spatial autocorrelation				
	Moran's I value	Observed	Expected	SD	p-value
Bridges	0.0336	0.0336	-0.2	3.72529e-09	1
Gap in medians	-0.0058	-0.0058	-0.0526	0.1266	0.7115
Industry/Institue/Intersections	-0.3021	-0.3021	-0.1667	0.1690	0.4229
bus or truck by	-0.4248	-0.4248	-0.25	0.3338	0.6006
Piligrimages/shandy/Tollplaza	-0.3000	-0.3000	-0.25	0.3449	0.8847

From the above analysis we can conclude that the safety related discrepancies showed different similarity indexes based on their dependency. Discrepancy due to bridge exhibits the perfect clustering or similar values or perfect precision. Whereas the other discrepancies Gap in median, industry, bus or truck lay by, toll plazas represented that the Negative correlation, it indicates that dissimilar values together in a map or perfect dispersion. Finally we can conclude that the discrepancies at various locations can cause the low safety. So, we try to identify the discrepancies based on the spatial data and finding the spatial dependencies among the groups together.

4. REFERENCES:

1. Ali Moradi, Hamid Soori, Amir Kavousi, Farshid Eshghabadi, Ensiyeh Jamshidi and Salahdien Zeini (2016). Spatial analysis to identify high risk areas for traffic crashes resulting in death of pedestrians in Tehran, Med J Islam Repub Iran, 30: 450.

2. Birch (1997). A New Data Clustering Algorithm and Its Applications. *Data Mining and Knowledge Discovery*, Volume 1, Issue 2.

3. Charankumar G and Shobhalatha G (2019). Analysis of water quality by using spatial graph theory and Metamodelling, Accepted for the possible publication in the journal of Thailand Statistician.

4. Charankumar G and Shobhalatha G (2019). An empirical study on shortest path for Graph clustering in Network analysis. Accepted for the possible publication in the Journal of Physics: Conference Series, IOP Publishing.

5. Charankumar G Shobhalatha G and Rajyalakshmi K (2019). Measuring spatial dependencies of various spatial objects related to the road safety discrepancies. International journal of innovative technology and exploring engineering research, 8, 11, 362-365.

6**.** Dale, M R J and Fortin, M J (2010. Transition from graphs to spatial graphs. Annual review of ecology, evolution and Systematics, Vol. 41, 1, P. No. 21-38.

7. Erica Flapan, Thomas W. Mattman, Blake Mellor, Ramin Naimi, and Ryo Nikkuni, *RECENT DEVELOPMENTS IN SPATIAL GRAPH THEORY*, Contemporary Mathematics, vol. 689, 2017, pp. 81-102.

8. Evans, J., and E. Minieka, Optimization algorithms for networks and graphs, 2nd Edition, Marcel Dekker, Newyork, 1992.

9. Fall, A., Fortin M. J., Manseau, M Obrien, D (2007). Spatial graphs: principles and application for habitat connectivity, Ecosystem, 10, 448-461.

10. Fan, C., and Myint, S. (2014). A comparison of spatial autocorrelation indices and landscape metrics in measuring urban landscape fragmentation land scape and urban planning, 121, 117-128.

11. Griffth, D. A. (2011). Spatial autocorrelation and spatial filtering: gaining understanding through theory and scientific visualization. Berlin: Springer.

12. Gyananath, SR Islam and S.V.Shewdikar (2001), Assessment of Environmental Parameter on ground water quality, Indian Journal Of Environmental Protection, Vol.21, No.4, April 2001, pp.: 289-294.

13. John snow (1854) used a first Spatial graph based spatial analysis for Spatial graphing an outbreak of cholera and the spread of disease.

14. Kobayashi (1994). *On the spatial graph*, Kodai Math Journal, 17, 511-517.

15. Kamaldeep singh Oberoi, Geraldine Del Mondo, Yohan Dupuis and Pascal Vasseur (2017), Spatial modeling of urban road traffic using graph theory, SAGEO-Rouen, 6-9.

16. Li Honggei calder Caterine A (2007). Beyond Moran's/: Testing for spatial dependence based on the spatial autoregressive model, Geographical analysis, Vol. 39, 4, P. No. 357-375.

17. M.R.T. Dale and M.J. Fortin (2010), From Graphs to Spatial Graphs, Annual Review of Ecology, Evolution and Systematics, Vol. 41:21-38.

18. Moran, P. A. P. (1950), " Notes on continuous stochastic phenomena", Biometrika, 37, Vol. 1, P. No. 17-23.

19. Mark Altaweel (2017), GIS and spatial autocorrelation, spatial analysis.

20. Ore, O (1961). "A Problem regarding the tracing of graph", *Rev. elementary Math*., Vol. 6, 49-53.

21. Prudhomme O Mera, W., Platt, A. Naanyu, V., Cole, D. and Ndeges, S. (2013). Spatial autocorrelation in uptake of antenatal care and relationship to individual household and village level factors: Results from a community based survey of pregnant women in six districts in western Kenya.

22. P. Praveen and B. Rama (2017). A K- Means Clustering algorithm on Numeric dat, International journal of Pure and applied mathematics, V0l. 117, No. 7, P. No. 157-164.

23. Russell R. Barton (2015). *Tutorial: simulation metamodeling*, Proceedings of the 2015 Winter Simulation Conference L. Yilmaz, W. K. V. Chan, I. Moon, T. M. K. Roeder, C. Macal, and M. D. Rossetti, eds.

24. Saurav Kaushik (2016). An Introduction to clustering and different methods of clustering.