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Geoinformatics in sprawl modelling- An overview

Ammu Johny[1], Maya Mary mathews[2]
[1]*(Department of Civil Engineering, Sree Narayana Gurukulam College of Engineering, Kerala, India)*
[2]*(Department of Civil Engineering, Sree Narayana Gurukulam College of Engineering, Kerala, India)*

Abstract: *Urban sprawl refers to the extent of urbanization. It is considered one of the most potential threats to sustainable development of a region. Unplanned and unprecedented growth of urbanization has proven to consume important land-use such as vegetation, agriculture and wetland. Sprawl is known to curb balanced resource allocation and infrastructure facilitation. It is of considerable importance to have an idea about the magnitude, direction and potential sprawl that might occur, before preparing a master plan for development. With the advance of geospatial technology it is now possible to study the history of urbanization of a region and to predict the future sprawl. Geographical Information System and Remote Sensing have been made use in this direction. This paper reviews the application of geo-informatics in combination with methods such as artificial neural network, arithmetical hierarchy process, cellular automata, landscape metrics and regression analysis in a number of cases of sprawl phenomenon. A wide range of successful studies and their prediction models have been discussed. Spatial and temporal analysis based on built-up provide a good measure that can help understanding the degree of urban sprawl and to prepare a model that can project future sprawl. Prediction models for sprawl were mostly combinations of spatial and attribute data except a few cases of solely spatial models.*

Keywords - *GIS; sprawl; urban; spatial data*

I. Introduction

Urban sprawl refers to the extent of urbanisation, which is a global phenomenon mainly driven by population growth and large scale migration (S.Tamilenthi et al. 2011). A general consensus regarding the definition and impact of urban sprawl has not been achieved yet (Johnson, 2001). The causes of urban growth are quite similar and highly interlinked with those of sprawl making it difficult to distinguish the two. However, it is important to realise that urban growth may be observed without the occurrence of sprawl. Some of the causes, for example population growth, may result in coordinated compact growth or uncoordinated sprawled growth. Urban sprawl is referred to as uncontrolled, scattered suburban development that increases traffic problems, depletes local resources, and destroys open space (Peiser, 2001). It may be regarded as the scattering of new development on isolated tracts, separated from other areas by vacant land (Lata, et al. 2001). It has also been described as leapfrog development (Jothimani, 1977; Torrens and Albert, 2000). It involves the migration of a population from populated towns and cities to low density residential development over more and more rural land. The end result is the spreading of a city and its suburbs over more and more rural land. Batty et al. defined sprawl as "uncoordinated growth: the expansion of community without concern for its consequences, in short, unplanned, incremental urban growth which is often regarded unsustainable.

In developing countries like India, a major proportion of the population lives in urban areas or regularly commutes in and out of urban areas. Urban sprawl poise to handicap effective allocation of limited resources and infrastructure facilitation becomes challenging to the authorities. Sprawl possess to threaten every chance of sustainable development of a country as it encroaches in to other important landuses such as agriculture, wetland, forest, open spaces and recreational parks. In order to prevent this type of growth, monitoring urban development through measures such as legislation, zonation, preparing master plan etc. has become imperative. But for incorporating necessary measures it is required to know the history, current dynamics and future potential of sprawl that might occur in the area.

The purpose of this review paper is to provide critical, constructive analysis of the literature studying urban sprawl using geoinformatics through summary, classification, analysis, comparison. It aims to organize, evaluate, synthesize, and identify patterns and trends in the related research. The paper will also help to identify research gaps and recommend new research areas. Due to repetition of concepts, works having technical similarity with the papers discussed here were avoided from this discussion.

II. Spatio-temporal study of urban sprawl

A major culprit causing unhealthy urban sprawl is poorly planned urban land use and economic activity (Pendall, 1999). Urban sprawl is often evaluated and characterized exclusively based on major socioeconomic indicators such as population growth, commuting costs, employment shifts, city revenue change, and number of commercial establishments (Brueckner, 2000; Lucy & Phillips, 2001). But in order to understand urban sprawl as a phenomenon it is necessary to present urban sprawl in a spatial context. Remote sensing and GIS has been used to detect urban land cover changes in relation to urbanization and has proved to be efficient tools in doing so. In the recent years remote sensing images with better resolutions are available for such studies. Remote sensing and GIS has been used separately as well as in combination to understand sprawl. Using remote sensing technique has the advantage of providing data to study the spatiotemporal trends of urban sprawl using multi-stage images, providing a basis for projecting future urbanization. GIS on the other hand provides numerous tools for analyzing of raster as well as vector data.

III. History of sprawl studies

How to measure urban sprawl has been always a matter of difference between researchers. Some organizations have put forward their indicators for quantifying urban sprawl. Besides, there are studies which focus on using indicators to measure urban sprawl by establishing multi-dimensional indicators by GIS analysis (Ewing, R. P., Don Chen. 2002), (Frenkel, M. A. 2005),(Galster, G. et al. 2001), (Kent B. Barnes et al. 2001), (S.Fina, S.Siedentop. 2008), (Song Y, G.-J. Knaap. 2004), (Schneider A, C. E. W. 2008), (Tsai, Y.-H. 2005). Remote sensing and GIS can be separately or in combination for application in studies of urban sprawl. There are some researches on how to use remote sensing and GIS to monitor and measure urban sprawl (Jingnan Huanget al.. 2007), (Anthony Gar-On Yeh, Xia Li. 2001), (Li, Y. a. X. 2001), (H. S.Sudhira at al. 2004), (Wei Ji, J. M. et al. 2006), (Xi Jun Yu, C. N. Ng. 2007), (Mahesh Kumar Jat et al. 2008). The built-up area is generally considered as the characteristic of urban area (Barnes et al., 2001; Epstein et al.,2002). It is measured by considering the increase in the built-up as the key feature of sprawl, which is delineated from maps/toposheets or from satellite imageries (H. S. Sudhira at al. 2004). The convergence of GIS, remote sensing and database management systems has helped in quantifying, monitoring, modelling and subsequently predicting this phenomenon (H. S. Sudhira at al. 2004).

H.S. Sudhira et al. (2005) studied the pattern and extent of sprawl in Mangalore, Udupi region in Karnataka, India. A buffer region of 4 km on each side was marked for detailed investigation of sprawl over the period of three decades (1972–1999). GIS and remote sensing data along with collateral data were used in analysing the growth, pattern and extent. The data collected were the Survey of India toposheets, the multispectral satellite imagery of the Indian Remote Sensing (IRS) satellite, LISS-3, the demographic details etc. The multispectral LISS satellite imagery was subjected to analyses including bands extraction, restoration, classification, and enhancement. The Gaussian maximum likelihood classifier (MLC) was employed for classification. The study describes some of the landscape metrics such as Shannon's entropy, patchiness and map density required for quantifying sprawl. In order to explore the probable relationship of percentage built-up with causal factors of sprawl (population, population densities, annual population growth rate, distance from Mangalore and distance from Udupi etc.), regression analysis was undertaken (linear, quadratic, exponential and logarithmic). Regression analyses revealed the individual contribution by the causal factors and the most significant relationships were outlined. The result proved that the sprawl declines with increase in distance from urban centers. To assess the cumulative effects of causal factors, stepwise regression analysis considering multivariate was done assuming the relationship between variables to be linear. From among the many equations formulated, best model to represent urban sprawl was selected based on the highest correlation coefficient. This model was used to project the built-up for 2020 and 2050. It was found that the percentage built-up for 2020 and 2050 would be 18.10 and 30.47%, respectively. This study received a general acceptance among various research communities for being able to quantify sprawl with better clarity which was lacking in many of the contemporary works. However, this study could not provide a graphical representation of sprawl so as to know which areas were more susceptible to sprawl.

Wei Ji et al. (2006) applied the spatial analytical methods to identify both general trends and more subtle patterns of urban land changes. Landsat imagery of metropolitan Kansas City, USA was used to generate time series of land cover data over the past three decades. Based on remotely sensed land cover data, landscape metrics were calculated. Both the remotely sensed data and landscape metrics were used to characterize long-term trends and patterns of urban sprawl. The 1972, 1979, and 1985 images were resampled in post-classification using the nearest neighbour interpolation to match the remaining images of 30 m x 30 m spatial resolution. The land cover classification at the metropolitan level was conducted using the supervised maximum likelihood classification method. For the purpose of characterizing urban sprawl, four major types of land cover were identified: built-up area, forestland, non-forest vegetation, and water body. During the supervised classification, a spectral signature file was generated and used for each of the six images. Based on the remotely sensed land cover data, selected landscape metrics were calculated using the FRAGSTATS program (McGarigal & Marks, 1995) for each of the selected cities and counties, at the landscape (metropolitan) level, and for each of four directional sectors of the metropolitan area. The metrics include the patch density (PD) index of the built-up land cover as well as the patch density, the largest patch index (LPI), and the aggregation index (AI) of both forestland and non-forest vegetation. The neighbor rule was applied to link certain adjacent pixels to form a patch, further reducing the occurrences of patches with a single pixel or a small number of pixels to reduce the impact of the ''salt-and pepper'' effect. Both the remotely sensed data and landscape metrics were used to characterize long-term trends and patterns of urban sprawl. Land cover change analyses at the metropolitan, county, and city levels reveal that over the past three decades the significant increase of built-up land in the study area was mainly at the expense of non-forest vegetation cover. The spatial and temporal heterogeneity of the land cover changes allowed the identification of fast and slow sprawling areas. The landscape metrics were analyzed across jurisdictional levels to understand the effects of the built-up expansion on the forestland and non-forest vegetation cover. The results of the analysis suggested that at the metropolitan level both the areas of non-forest vegetation and the forestland became more fragmented due to development while large forest patches were less affected. The interpretation of the built-up patch density metrics helped identify different stages of urbanization in two major urban sprawl directions of the metropolitan area. Land consumption indices (LCI) were devised to relate the remotely sensed built-up growth to changes in housing and commercial constructions as major driving factors. This study was aimed only at characterizing urban sprawl from historical data and studying its trends.

Shamsaini Shamsuddin et al. (2007) conducted a case study of Seremban district, Malasya as an attempt towards predicting and simulating future land use pattern. The integration of statistical modeling technique via binary logistic regression analysis with GIS technology in understanding and predicting urban growth was done. The urban transition probability map generated from the regression model was used as the basis to map the extent of urban area for the predicted year. Here, the spatial sequence of future urban development was assumed to follow the descending order of the transition probabilities values. This means that land cells with higher transition probability values will develop first. So, in predicting the urban extent for the specified period, the selected of the land cells to be converted to urban use for the predicted year will stop when the size of the demanded area is met. Basing on the parameters derived from the predictors that significantly influence urban land development, areas that have high probabilities to be converted to urban land use in the future, i.e. The "hot spots" for land use changes are identified. The result shows that urban land use pattern in the study area within the study period are significantly related to more than half of the predictors used in the analysis. Such information will indicate where priority for planning and further research should be focused. Apart from that, basing on the information derived, future urban land pattern of the area concerned could be predicted.

D. Stevens et al. (2007) proposed a tool, named iCity or Irregular City, extends the traditional formalization of cellular automata (CA) to include an irregular spatial structure, asynchronous urban growth, and a high spatio-temporal resolution to aid in spatial decision making for urban planning. The iCity software tool was developed as an embedded model within a common desktop geographic information system (GIS) with a user-friendly interface to control modelling operations for urban land-use change. This approach allows the model developer to focus on implementing model logic rather than developing an entire stand-alone modelling application. It also provides the model user with a familiar environment in which to run the model to simulate urban growth. iCity was developed as an ArcGIS software extension to demonstrate how a common desktop GIS can be used to help enhance the existing range of urban planning software tools. The iCity prototype was developed to explore how a recently updated GIS software package can be used for integrating a high-resolution irregular CA modelling approach with a common desktop GIS to aid in the urban planning process. Because ArcObjects are the same software libraries on which the ArcGIS suites of applications are built, any function available in ArcGIS can be implemented programmatically through ArcObjects. This study proposes iCity, a GIS-based tool that builds upon CA theory to predictively model urban growth using an irregular spatial structure, high-resolution spatial data at the cadastral level, and a high temporal resolution. Future research is required to take the model logic from its current stage in a proof-of-concept model to a more robust logic capable of being used as a part of a spatial decision support system.

Sandeep Maithani et al. (2007) used remote sensing data to provide the empirical inputs about urban growth and other spatial information. GIS is used for handling of this spatial data, to obtain site attributes and training data for neural network, and to provide spatial functions for constructing the model. The spatial database consisting of land use maps of different years and various spatial variables were generated by visually interpreting the following temporal time series remote sensing data and converting the analogue maps into digital format in Arc / Info software: IRS-1D, PAN + LISS-III merged imagery; and Land use / Land cover Map of 1993 based on field survey and Aerial Photographs of 1988. Standard GIS operations like Euclidian distance, focal sum, etc; were carried out to retrieve site attributes such as distance to major roads and minor roads, amount of built up in neighbourhood, etc; and to prepare training data for ANN. A total of five spatial variables were chosen for the simulation of urban growth. The Artificial Neural Network is used to reveal the relationships between future urban growth probability and site attributes, as ANN can capture the non–linear complex behavior of urban systems. A three layer feed forward neural network architecture is used in this study. The model results are evaluated using the percent correct match (PCM) metric and Moran spatial autocorrelation index. The percent correct match (PCM) metric has been adopted to address the issue of model accuracy. In the percent correct match (PCM) metric cells that were predicted to transition t built-up (by the model output) are compared to the cells that actually did transition during the same period of study. Moran spatial autocorrelation index has been calculated for the simulated 2001 and actual 2001 built up area in order to measure how accurately the model has been able to predict the urban spatial pattern or morphology. The proposed model has successfully coupled the GIS environment and the ANN. The model was applied to simulate the urban growth of Saharanpur city in Uttar Pradesh.

Jiang Dong et al. (2008) evaluated the landuse suitability for urban growth of Jingjinji area, China. Using remote sensing and geographic information system (GIS) techniques. An integrated evaluating model was developed containing 9 factors belong to 3 categories, (1)environmental background factors, including elevation, slope, geomorphological types, accumulated temperature and wetness index; (2) water/land resources, including Precipitation, river density, land use; (3) socioeconomic, including railway density, road density, and population density. Land use data for 2005 were obtained from Landsat TM data through human-computer interactive interpretation. Six land use types were identified viz; cultivated land, woodland, grassland, water, urban and rural settlements and barren land. The analytical hierarchy process (AHP) method was adopted to derive weights to the parameters by the pair-wise comparison procedure and establish the weighting matrix. The urban development suitability index (UDSI) was calculated using this model. According to the UDSI result, the spatial distribution of urban development suitability and its driving forces were analyzed. Urban boundaries in 1995, 2000 and 2005, which were derived from Landsat TM/ETM+ satellite data, were overlaid on the UDSI map. It was found that the built-up areas of Beijing city have increased dramatically from 1990 to 2005. The analysis results together with the urban planning policy in this area, it was found that the most suitable areas can meet the needs for future urban expansion within the coming 5-10 years.

X. Zhang et al. (2008) tried to develop and assess a pattern analysis for land cover maps. The study made use of selected landscape metrics (PD, CONTAG, PAFRAC, and SHDI) for the multi-temporal land cover maps based on Landsat MSS/TM remote sensing during 1978-2004. This study systematically explores and compares trends and patterns of urban sprawl across the town level in Wujiang.

Rajesh Bahadur Thapa et al. (2008) stated that quantifying landscape pattern and its change are essential for the monitoring and assessment of environmental consequences of urban area. This paper analyzes spatiotemporal patterns of urban landscape changes in Kathmandu Valley, Nepal by combining remote sensing, GIS and landscape metrics. Multi-temporal satellite images from high resolution (CORONA, SPIN and IKONOS) to moderate resolution (Landsat : MSS, TM) were processed to identify the temporal changes in landscape patterns. Four land use maps were prepared from the images for the year 1967, 1978, 1991 and 2000. A set of landscape metrics was used to evaluate temporal dynamics of land uses from the maps at class and landscape levels.

B. Bhatta et al. (2008) stated that urban growth can be mapped, measured and modelled by using remote sensing data and GIS techniques along with several statistical measures. In this study three temporal satellite images of 15 years interval (1975, 1990 and 2005) were classified to determine the urban extent and growth of Kolkata-Howrah (West Bengal, India) in eight different directions within a circular region. Pearson's chi-square test and Shannon's entropy method have been applied to calculate the degree-of-freedom and degree-of-sprawl towards the analysis of urban growth.

H. Taubenbock et al. (2009) suggested that by classifying urban footprints since the 1970s using time-series of Landsat data, it is possible to detect temporal and spatial urban sprawl, redensification and urban development in the tremendously growing 12 largest Indian urban agglomerations. A multi-scale analysis aims to identify spatiotemporal urban types. In this study, the combination of absolute parameters (e.g. areal growth or built-up density) and landscape metrics (e.g. SHAPE index) were used quantitatively characterise the spatial pattern of the cities.

Mahesh Kumar Jat et al. (2010) suggested that the concentration of people in densely populated urban areas, especially in developing countries, calls for the use of monitoring systems like remote sensing. Such systems along with spatial analysis techniques like digital image processing and geographical information system (GIS) can be used for the monitoring and planning purposes as these enable the reporting of overall sprawl at a detailed level. In this work, urban sprawl of the Ajmer city(situated in Rajasthan State of India) has been studied at a mid scale level, over a period of 25 years (1977–2002), to extract the information related to sprawl , area of built-up surfaces and their spatial and temporal variabilityStatistical classification approaches were used for the classification of the remotely sensed images obtained from various sensors viz. Landsat MSS, TM, ETM+ and IRS LISS-III. Urban sprawl and its spatial and temporal characteristics were derived from the classified satellite images. The Shannon's entropy and landscape metrics (patchiness and map density) were computed in terms of spatial phenomenon, in order to quantify the urban form (impervious area). Further, multivariate statistical techniques were used to establish the relationship between the urban sprawl and its causative factors. Results revealed that land development (160.8%) in Ajmer was more than three times the population growth (50.1%). This work was more or less similar to that undertaken by the same author along with H.S. Sudhira et al. (2005).

Saravanan. P et al. (2010) conducted research to identify Urban Sprawl Pattern for Madurai Region Using GIS which focussed on the nature and pattern of urban expansion of Madurai city over its adjacent region during the period from 1991 to 2006. Satellite product used for the analysis of sprawl was LANDSAT imagery. The development of road network was obtained from toposheet and GeoEye imagery of Google earth. The temporal analysis of landuse / landcover of the sample villages were done for the period 1991 and 2006 using LANDSAT TM and LANDSAT ETM+ images. Based on its proximity to the Madurai city, the rural urban fringe was fragmented into two zones namely Ring I and Ring II. In order to identify the factors responsible for the urban sprawl of Madurai city, two sample villages from the respective zones were selected. The study indicated that road transport was solely responsible for the rapid urban development in the sample villages. In addition, GIS based analysis of the pattern of urban expansion over the demographic change and landuse modifications indicated that urban growth has mainly taken place linearly along the major roads in the study area.

Rajesh Bahadur Thapa et al. (2011) stated that the complexity of urban system requires integrated tools and techniques to understand the spatial process of urban development and project the future scenarios. The research was aimed at simulating the urban growth patterns in Kathmandu metropolitan region in Nepal. Based on the historical experiences of the land use transitions, weight of evidence method integrated in cellular automata framework was adopted for predicting the future spatial patterns of urban growth. Three land use maps at 30 m spatial resolution for the years 1978, 1991, and 2000 were processed using remote sensing techniques. Furthermore, the land cover transition rates for each category were computed normalizing row sum equal to 1. As the model was set to run in yearly time steps, the transition rates were further converted to annual rates by simply dividing the year differences, i.e., 13 and 9 for the land cover transition period of1978–1991 and 1991–2000, respectively. The transition rates per year were passed to the modeling as fixed parameters. After creating all the required input maps in ArcGIS software, a simulation model of urban growth was designed in DINAMICA, a spatially explicit CA based modeling software. The DINAMICA model allocated the changes across the landscape based on spatial data layers representing physical and socioeconomic conditions which are stored in a GIS environment. As interactions between landscape elements occur in different ways, depending on local characteristics and transition rates, DINAMICA model produces distinct spatial patterns of land cover change. We extrapolated urban development patterns to 2010 and 2020 under the current scenario across the metropolitan region. Depending on local characteristics and land cover transition rates, this model produced noticeable spatial pattern of changes in the region. Based on the extrapolated spatial patterns, the urban development in the Kathmandu valley will continue through both in-filling in existing urban areas and outward rapid expansion toward the east and south directions. Overall development will be greatly affected by the existing urban space, transportation network, and topographic complexity.

Atiqur Rahman et al. (2011) attempted to use Shannon’s entropy model to assess urban sprawl using IRS P-6 data and topographic sheet in GIS environment for Hyderabad and its surrounding area. The study shows that there is a remarkable urban sprawl in and around the twin city between 1971 and 2005.

Qihao Weng (2011) concluded that remote sensing of built-up surfaces in the urban areas has recently attracted unprecedented attention. In this paper, various digital remote sensing approaches to extract and estimate built-up surfaces will be examined. In particular, the impacts of spatial, geometric, spectral, and temporal resolutions on the estimation and mapping was addressed, so was the selection of an appropriate estimation method based on remotely sensed data characteristics. Techniques, such as data/image fusion, expert systems, and contextual classification methods, have also been explored. He also suggested that majority of research efforts have been made for mapping urban landscapes at various scales and on the spatial resolution requirements of such mapping.

Jiangfeng Li et al. (2011) in their study investigated land use changes, and their ecological effects in Wuhan (1987-2005). Remote Sensing techniques extracted land use data, whilst the spatial analyst software FRAGSTATS, quantified and explained land use changes and their effects in Wuhan.

A GIS-based buffer gradient analysis on spatiotemporal dynamics of urban expansion in Shanghai and its major satellite cities was done by Xiaowen Li et al. (2011). In this study, a combination of remotely sensed data, urbanization metrics and GIS based buffer gradient analysis is employed to analyze the overall spatiotemporal characteristics of urban expansion in the Shanghai region, China, and to explore the urbanization of its major satellite cities and their interactions. Four sets of Landsat TM images were used in this study (1987/1990/1995/2000, resolution 30 m, seven bands). These images were processed with ERDAS IMAGINE software, which involves geometric correction, unsupervised and supervised classification, and GIS reclassification. The images were rectified to a Gauss-Krüger projection based on 1:50,000 scale topographic maps using second order polynomial geometric model and cubic convolution algorithm. Through the use of spectral classification, the urban area was extracted, which included high density residential areas and new development zones. To measure and quantify the magnitude and pace of urban growth, an urbanization proportional index (UPI) and urbanization intensity index (UII) were developed and employed. GIS-based buffer analysis was adopted in our research, which involved circular buffer zones surrounding the city center. Each buffer zone was employed as a basic spatial unit to characterize distance-dependent urban growth behavior with their UPI and UII values for a given time period. Two different buffer systems were established, one was a buffer zone system with a width of 2 km covering the entire region designed to explore the overall urbanization process over the metropolitan area of Shanghai. The other buffer system was established by delineating separate buffer zones to compare spatiotemporal characteristics of urban growth between the Shanghai urban center and the eight major satellite cites. The results showed that the changes in the urbanization gradient are largely influenced by the distance from the urban centre, yet there are distinct spatial variations mainly resulting from the interactions of the urbanization of the central city with that of satellite cities. The urbanization within the urban-suburb transitional zones generally had a specific rhythm of intensity and weakness, which can function as the spatial signatures to analyze and demonstrate similar or other types of urbanization processes. The major satellite cities of the Shanghai region showed their distinct temporal-spatial characteristics and were categorized as autonomous, passive, steady and irregular modes of urbanization.

Mahmoud Mohammadi et al.(2013), developed a model based on CA, AHP and GIS for simulation of urban sprawl phenomenon in 8th and 12th municipal districts of Isfahan, Iran. Distance from highways, distance from roads, distance from residential areas, distance from urban infrastructures and distance from educational land use were selected as the factors affecting simulation of urban growth and their weights were calculated by AHP. Pair-wise comparisons of the affecting factors were conducted to obtain weight and the effect of each factor on urban growth process using Delphi technique and the Expert Choice software. Then, a standalone CA was developed and simulation was performed for 2012 based on the data of 2005. By calculating the Kappa coefficient the accuracy of the model was demonstrated. The results suggested that the combination of indicated models can provide an appropriate tool for urban planners to profoundly analyze and predict urban growth process.

Menaka Chellasamy et al. (2015) devised a neural-evidence pooling approach to predict urban sprawl using multi-temporal remote sensing data. The research introduces a dynamic neural network based technique to predict the urban growth in Sriperumbudur taluk, India. The novelty of this technique is integration of neural network and theory of evidence to predict future growth which does not require any definition of input parameters, spatial rules or large dataset that involves expert knowledge and time consuming manual work for preparation. Land Use Land Cover (LULC) images were created by classifying LANDSAT TM satellite image of 30m spatial resolution captured in the year 1991, 2000 and 2009 using Multi-Layer-Perceptron (MLP) neural network. Five spatial metrics namely Shannon's entropy, aggregation index, density, nuclearity, and proximity are derived around each non-urban pixel in 2009 by considering 7x7 window of spatial unit in the LULC images of the three years. These metrics are fed to Focused Time Delay Neural Network (FTDNN) and the metrics for year 2018 are predicted. Finally, evidence pooling is applied to the predicted metrics to identify whether the non-urban pixels in 2009 changes to urban pixel in the year. The predicted results shows that 12.5% of nonurban LULC mainly agriculture and wasteland in 2009 will change to urban land use in 2018. The results potentially help the city planners and developers to have prior visualization of future urban sprawl in the study area for effective city planning.

IV. Conclusion

Remote sensing and GIS can be separately or in combination for application in studies of urban sprawl. In this work, an attempt was made to identify the best way to monitor and measure urban sprawl through extensive literature review. Some research organizations have put forward their indicators for measuring urban sprawl. Besides, many works focused on using indicators to measure urban sprawl by establishing multi-dimensional indicators by GIS analysis or descriptive statistical analysis. Some researchers have phenomenon is simulated geometrically using techniques of cellular automata (CA). The CA technique is used extensively in the urban growth models and in urban. The inadequacy in some of these is that the models fail to interact with the causal factors driving the sprawl such as the population growth, availability of land and proximity to city centres and highways. The spatial logistic regression technique used for analysing the urban growth pattern and subsequently model the same. The inadequacies in their technique related to accurately pinpoint spatially where the sprawl would occur. This problem was effectively addressed when neural network is applied to the remote sensing data especially for classification and thematic representation in combination with cellular automata and AHP. It was found that the neural spatial interaction models would relieve the model user of the need to specify exactly a model that includes all necessary terms to model the true spatial interaction function.

Table 1: Comparison between various researches

Researcher	softwares used	Remote sensing imagery used	metrics used	Method of study	Validation
H.S. Sudhira et al. (2005)	MAPINFO 5.5, Idrisi 32	(IRS) LISS-3	Shannon's Entropy, Patchiness And Map Density	Stepwise regression analysis	Correlation factor
Wei Ji et al. (2006)	ArcGIS (ESRI, Inc.), ERDAS IMAGINE (Leica, Inc.)., FRAGSTATS	Landsat -1 and Landsat -3 Multispectral Scanner (MSS)	Patch Density (PD), The Largest Patch Index (LPI), And The Aggregation Index (AI)	Land consumption indices (LCI)	Correlation factor
Sandeep Maithani et al. (2007)	Arc / Info software	IRS-1D, PAN + LISS-III MERGED imagery	_	Artificial neural network (ann)	Percent correct match (PCM) metric and Moran spatial autocorrelation index
Shamsaini Shamsuddin et al. (2007)	_	Landsat TM/ETM+	_	Binary logistic regression analysis,urban transition probability map	Correlation factor
D. Stevens et al. (2007)	ArcGIS, ArcObjects	IKONOS	_	Icity or Irregular City developed software using cellular automata (CA)	_
Jiang Dong et al. (2008)	_	Landsat TM/ETM+	Urban Development Suitability Index (UDSI)	Analytical hierarchy process (AHP)	_
X. Zhang et al. (2008)	_	Landsat MSS/TM	PD, CONTAG, PAFRAC, And SHDI	_	_
B. Bhatta et al. (2008)	_		Shannon's Entropy	Pearson's chi-square test	The degree-of-freedom and degree-of-sprawl

Mahmoud Mohammadi et al.(2013)	matlab, Expert Choice software, GIS	_	_	Delphi technique, CA, AHP and GIS	Kappa coefficient
Menaka Chellasamy et al. (2015)	_	LANDSAT TM	Shannon's entropy, aggregation index, density, nuclearity, and proximity	Multi-Layer-Perceptron neural network, Focused Time Delay Neural Network	_
Xiaowen Li et al. (2011).	ERDAS IMAGINE	_	urbanization proportional index, urbanization intensity index	buffer gradient analysis	_

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