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GIS AND STOCHASTIC BASED ASSESSMENT AND MODELLING OF URBAN GROWTH PATTERNS - A REVIEW

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ABSTRACT

As the world's population is increasing dramatically, even the most fragile ecosystem of the earth such as the Himalayas is not safe and is deteriorating with each passing day which requires urgent attention. So, Remote Sensing and GIS strategies comes to rescue as a critical and well-known approaches that have been utilized lately to map and measure metropolitan development designs. This paper essentially expects to give a premise to a literature review of metropolitan development planning and measuring by utilizing various approaches. For this reason, the overall qualities of mapping and measuring metropolitan growth pattern are portrayed and grouped. The qualities and shortcomings of the different methods have been recognized from an analysis and scrutiny of the attributes of the methods. Aftereffects of review affirm that consolidating qualitative and quantitative approaches, for example, Shannon entropy method and change detection, to quantify and map urban development pattern will work on comprehension of the peculiarity of metropolitan development. Additionally, utilizing social and financial information, for example, census and income information will enhance the understanding of the connections among circumstances and end results. The coordination of social and financial elements with qualitative and quantitative approaches will add to an ideal assessment of urban development pattern and land use changes, considering nominal, social, monetary, spatial, and transient variables into account.

KEYWORDS: Urban Expansion, Shannon's Entropy, AHP, Cellular Automata, Markov Models

INTRODUCTION

In recent years, urban areas all over the planet have been confronting the issue of metropolitan development because of growing census and economic development. (Duranton & Puga, 2014).

Urbanization, alluding to a development in the extent of a populace living in metropolitan regions, is one of the major social changes clearing the globe. As per the most recent gauge and projection delivered by the Population Division, United Nations, the world's metropolitan populace keeps on developing at a higher rate than the complete populace of the world, and 3 billion individuals or around 48% of the total populace are presently city inhabitants (Chen, 2007) Urbanization has been a widespread and significant social and economic peculiarity occurring from one side of the planet to the other. This cycle, without any indication of dialling back, might be the most dominant and apparent anthropogenic power that has achieved basic changes in land use and scene design all over the planet. Quick urbanization, particularly in the developing regions, will keep on being one of the critical issues of worldwide change in the 21st century influencing the human aspects (Deng et al., 2009). The uncontrolled populace development and relocation in metropolitan regions have made the issues like of urban sprawl. Nonetheless, populace development and urban sprawl are straightforwardly reliant upon one another. In India level of urbanization expanded from 27.81% in 2001 to 31.16% in 2011 (Deep & Saklani, 2014). Urban sprawl which is the increase in population size in relation to both magnitude and direction can be considered as a negative outcome of urban growth. One of the negative characterizations of urban sprawl is its considerable contribution in climate change, and the most adverse ones are felt upon agriculture land, water bodies thereby changing the whole hydrological ecosystem (Maktav and Erber 2005). The example of urbanization in India is portrayed by constant grouping of populace and exercises in huge urban communities. Kingsley Davis utilized the expression "over-urbanization "where in metropolitan wretchedness and rural destitution exists next to each other (Kingsley Davis and Golden, 1954). One more researcher named Breese portrays urbanization in India as pseudo-urbanization wherein individuals show up at urban communities not because of metropolitan force yet because of rural push factors (Breese, 1969) Discussion shows useless urbanization and metropolitan growth which brings about a convergence of populace in a couple of huge urban areas without a comparing expansion in their economic base. Urbanization process isn't primarily "migration drove" however a result of demographic blast because of natural growth. Additionally, rural out-relocation is coordinated towards class I urban communities (Premi, 1991). The enormous urban communities achieved exorbitantly huge populace size prompting virtual breakdown in the metropolitan administrations and standard of living. Enormous urban areas are primarily frail and formal as opposed to being utilitarian substances in view of deficient economic base. The metropolitan populace in India has gone up bit by bit from around 11% in 1901 to 17 percent in 1951 and afterward to 28 percent in 2001. The metropolitan development rate during 1941–51 was genuinely high at 3.5 percent per annum, however at that point diminished to 2.3 percent in the next decade. It has been brought up that the figure for the 1940s was on the high side, since the meaning of metropolitan focus couldn't be normalized in the first Census conducted after Freedom and furthermore in light of the fact that huge country rural–urban migration happened because of segment of the country. The most noteworthy pace of metropolitan development (3.8 percent) was recorded during the 1970s, yet has along these lines diminished to 3.1 percent during the 1980s and 2.7 percent during the 1990s. (Jaysawal & Saha, 2014). India's urbanization is trailed by some essential issues in the field of lodging, slums, transport water supply, disinfection, water contamination, air contamination, lacking arrangement for social framework (school, medical clinic, and so on) Class I urban areas like Calcutta, Bombay, Delhi, Madras have arrived at immersion level of business creating limit. Since these urban areas are experiencing urban poverty, joblessness, lodging deficiency, emergency in metropolitan infrastructure, these huge urban communities can't assimilate these distressed rural transients i.e poor landless unskilled and incompetent farming workers (Kundu, 1994). Indian urbanization is involuted not evolute (Mukherjee, 1995). Poverty prompted migration happens because of country push factors. Megacities develop in urban populace not in urban thriving, and culture (Nayak, 1962). Consequently, it is urbanization without metropolitan functional attributes. These super urban communities are dependent upon outrageous filthy slum and exceptionally savage super city denying shelter, drinking water, power, disinfection to the super poor and rural migrants (Kundu, A, N. Sarangi and B.P Dash 2003). With changes in the land-use design when the city expands in size, it extends both horizontally and vertically. The horizontal development inundated the close by periphery villages and changed over the farming terrains, so that there is decline in water level. Along these lines, there are chances of pollution of drinking water as a result of spillage of lines. Something else worth thought is land esteem which is valued as a result of shortage of land in the developing metropolitan places. In this manner, there is mushrooming development of lofts and in busy centres; the flats are given authorization without actually taking a look at the method of sewage facilities (Jaysawal & Saha, 2014). Thus, the urban growth monitoring has turned into a significant utilization of remote sensing and Geographic Information System (GIS). Growth Monitoring is the method involved with deciding as well as portraying changes in land-cover and land-use design reliant upon co-enlisted multi-temporal remotely detecting data. The key explanation in including remote sensing for change recognition is that the cycle can recognize change between somewhere around two dates that is special of normal assortment. Different examiners have settled the issue of definitively investigating land-cover and land-use change in a wide assortment of conditions (Hegazy & Kaloop, 2015).

Analysing the impact of Urbanization on climate through RS & GIS

(Oswald et al., 2020) discusses about the increasing paces of urbanization have prompted an expansion in impenetrable regions that effect or adjust the nearby surface energy balance. Thus, metropolitan regions are inclined to higher encompassing air temperatures than encompassing country regions, a phenomenon regularly alluded to as the Urban Heat Island (UHI) impact. The UHI impact scales with city size and is adjusted by the surrounding territory and surface construction of the metropolitan settlement.

(Mustafa et al., 2020) shares attentions on Climate change as one of the most basic difficulties that the world countenances. Past studies have revealed that environment change significantly affects the land surface temperature and its different boundaries. Development of metropolitan regions is viewed as a critical variable for the adjustment of land use and land surface temperature. Past investigations show that, in China, urban development and climate change counting temperature change are serious issues coming about from economic and social turn of events. Therefore, it is imperative to research ways of foreseeing change in land surface temperature (LST) change.

(Dhanaraj & Angadi, 2020) - Urban growth studies were most frequently conveyed out utilizing time series, medium resolution satellite imagery. A wide scope of satellite imagery classification techniques, for example, supervised, unsupervised, and non-parametric methodologies, which use diverse rationale to group the information in satellite imagery, are utilized in image classification. The Maximum Likelihood Classifier is the most frequently involved calculation in combination with supervised classification

(Lee, 2014) - Expansion in anthropogenic impacts and other environmental changes make a climate to a hurtful Urban Heat Islands. Land Surface Temperature (LST) which we can see through remote sensing data. It contrasts from the ordinary air temperature. LST can likewise be meant as surface's skin temperature. At the point when there is an unequal ecological circumstance like change in vegetation cover, climatic changes, increase in global warming and impacts due to hurtful mining exercises prompts flighty changes. In remote sensing, thermal infrared technology has revolved to be one of the huge sources to concentrate on the land surface's thermal attributes.

(Equere et al., 2021) - The utilization of remote-sensing driven LST for the UHI planning has been broadly embraced, on the grounds that it relates unequivocally with urbanization, which is a vital component in the development of the UHI. Consequently, huge headway has been made in investigating the flat metropolitan morphology highlights over the UHI utilizing the satellite or other airborne remote detecting advances, which have shown to be proficient in large scale data extraction. The developed (BU) file as a streamlined and more precise boundary for planning developed regions from a satellite picture, likewise fostered another list, normalized difference composite index (NDCI), for the programmed extraction of impenetrable surface (IS) regions from Landsat images while researching the effect of urbanization on the UHI in Ho Chi Minh City, Vietnam. In a comparative report, the urban thermal field variance index (UTFVI) was gotten from land surface temperatures by; to further develop portrayal of the urban heat island in their review. In another review, the unmanned aerial vehicle (UAV) was used in photogrammetry way to mapping of a site in Greece. The high-goal spatial pictures were utilized in concurrence with in-situ estimations to adequately characterize microclimates in light of surface emissivity esteems and temperature appropriations.

Katayama et al. (2000) saw that UI increments with building density and diminishes with NDVI in Tokyo Bay. Albeit the correlation amongst UI and temperature was not tried in past studies, the high prescient power saw in this review is on the grounds that regions with high density of buildings and low vegetation part are known to have high temperatures (Senanayake, et al., 2013; Zuvela-aloise et al., 2015)

Kawamura et al. (1997) likewise saw that UI was high in regions where residential energy and water utilization were high in Colombo, Sri Lanka. Studies have likewise shown that homegrown energy and water utilization increments with urban heat intensity, subsequently the high connection amongst UI and temperature. The UI was additionally observed to be high in bare regions thus upgrades its capability to anticipate temperature since bare and developed regions are relatively hot during the day (Srivanit, et al., 2012; Pu et al., 2006). In this manner, the near strength of the connection among UI and land cover properties improved its capability to map metropolitan development and comparing reactions of temperature.

MATERIALS & METHODS

Image Classification Techniques

Traditional Remote sensing data classification, techniques incorporate maximum-likelihood classifier (MLC), distance measure, clustering or logistic regression. Throughout the last ten years, further developed strategies, for example, decision trees, k-nearest-neighbours (kNN), random forest (RF), neural networks and support vector machines (SVM) have been utilized for LULC planning. In 2016, a review on the best in class of supervised methods for LULC grouping was performed. It was accounted for that SVM, kNN, and RF by and large gives preferable execution over other traditional classifiers, SVM being the most efficient technique (Carranza-García et al., 2019) The ARC/INFO GIS software package version 10 was utilized in the various phases of modelling, specifically, image processing, classified land cover and land use maps, and spatial analysis. For classification, the maximum likelihood classification technique, which is a supervised classification technique, was utilized for Landsat and Spot 5 space borne satellite pictures. The classified images were resampled to the same spatial resolution (30 m×30 m). The choice of the pixel size was planned to stay away from the reduction in spatial details of the images. In this way, the resampling step was led after image classification. Then, at that point, thematic raster maps of all factors were produced and determined in the Arc Info GIS climate, and introduced as raster maps with a matrix cell size of 30 m× 30 m (Alsharif & Pradhan, 2013). Supervised classification according is where "the user develops the spectral signatures of known categories, such as urban and forest, and then the software assigns each pixel in the image to the cover type to which its signature is most comparable". "Supervised classification is the process most frequently used for quantitative analyses of remote sensing image data". The supervised classification was applied after defined area of interest (AOI) which is called training classes. More than one training area was used to represent a particular class. The training sites were selected in agreement with the Landsat Image, Google Earth and Google Map (Rwanga & Ndambuki, 2017).

Unlike supervised classification, clustering methods (or unsupervised methods) require no training sets at all. Instead they attempt to find the underlying structure automatically by organizing the data into classes sharing similar, i.e. spectrally homogeneous, characteristics. The analyst 'simply' needs to specify the number of clusters present. Such procedures play an especially important role when very little a priori information about the data is available. Cluster analysis provides a useful method for organizing a large set of data so that the retrieval of information may be made more efficiently. A primary objective of using clustering algorithms for pre- classification of multispectral remote sensing data in particular is to obtain optimum information for the selection of training regions for subsequent supervised land-use segmentation of the imagery (Duda & Canty, 2002)

Contrasting to other traditional pixel-based classification, Object-Based Image Classification doesn't build single pixels. OBIC segments the whole raster image by categorizing pixels. Object-Based Image Classification (OBIC) method includes arrangement of pixels dependent on their spectral attributes, shape, texture and spatial relationship with the encompassing pixels and grouping them to create vector objects. In OBIC, objects are the key for classifying if one has the right image. A group of pixels in a map represents an image object. These groups of pixels or image objects occupy a distinct space within a landscape and can provide information about this landscape. OBIC tries to imitate the analysis done by human visual perception. (Walter, 2004)

STATISTICAL MODELS FOR MEASURING URBAN GROWTH

Logistic Regression

Urban development utilizing logistic regression is analysed, modelled and examined. The logistic regression model was applied to study the metropolitan development in Ahvaz, Khuzestan. The logistic regression focuses to find the relationship between metropolitan development and social, econometric and biophysical factors and to foresee the future metropolitan example. Logistic regression is one of the most well-known ways to modelling. This model can be utilized in modelling and analysing the relationship of a number of (Xs) independent factors to a dichotomous single dependent variable (Y), which addresses the event or non-event of an occasion. Strategic relapse tracks down the relationship between the independent factors and the function of the likelihood of an event happening observationally (Alsharif & Pradhan, 2013).

Shannon's Entropy

In order to measure and map urban morphology and urban sprawl, there are a variety of techniques that can be applied, such as shape index, contagion index, Shannon's entropy, Fractal analysis and Moran's I (Bhatta 2012; Munafo, Congedo 2013; Zeng et al. 2014). Among them Shannon's Entropy is applied in this case study. Shannon's Entropy is widely used to measure the spread of urbanization. It is one of the reliable methods to ascertain the degree of urban sprawl due to its robustness and relevance (Verzosa, Gonzalez 2010; Sarvestani et al. 2011). It is used to measure the degree of spatial dispersion and concentration exhibited by geographical variables among "n" number of spatial zone. The Shannon's Entropy can be expressed as:

$$- \Sigma \, Pi \, Log \, Pi$$

Where, Pi = the built-up area in the i zone / the total built-up area. (Yeh and Li 2001)

Landscape Metrics

Landscape Metrics are important in understanding landscape complexity and structural pattern. The quantification of the landscape structural pattern is obtained through landscape metrics algorithms. Generally, in order to quantify the categorical map pattern, surfeits of landscape metrics are developed. Landscape metrics aids in computation of two imperative attribute of landscape structure viz composition and configuration. Composition can be referred to as the features related with the overflow and assortment of patch types inside the scene however disregarding the spatial quality and areas or situation of the patches inside the mosaic. Then again, configuration characterizes the spatial arrangement, direction or position of patches inside the class or landscape (Mc Garigal and Marks 1995, Gustafson 1998).

Person's chi-square

Pearson's chi-square measurements consider the checking of opportunity among sets of factors decided to examine of a similar class of land-cover change. The mathematical expression: (observed expected) ²/expected. It uncovers the level of deviation for the observed metropolitan development over the expected. When observed and anticipated values are equivalent, the lower range is 0. This model was utilized to determine the provincial summation of level of deviation by Bonham-Carter and Almeida (Almeida et al., 2005 & Bonham-Carter, 1994). This study stretches out the model to dissect the pattern, process and the general circumstance of metropolitan extension.

Urban expansion intensity index (UEI Index)

During the process of metropolitan growth, because of the effect of road network, landscape, economic growth and social factors, the advancement frequently become unique in every bearing which be called inclination of metropolitan growth. Urban expansion intensity index can be utilized to dissect the spatial expansion contrasts of regional land utilize quantitatively and comprehend the inclination of metropolitan improvement in a certain time interval. It alludes to the rate that the metropolitan extension region involved of the aggregate land region in a particular region or a particular period (Ren 2013). The UEI can mirror the future course and capability of metropolitan development and it compares the magnitude and intensity of metropolitan land use in various periods. The division standard of UEI as: >1.92, high velocity development; 1.05-1.92, rapid development; 0.59-1.05, medium-velocity development; 0.28-0.59, low-speed improvement; 0-0.28, slow developments. The mathematical expression is:

$$UEI_{it} = \frac{\left[\left(ULA_{i,b} - ULA_{i,a}\right)/t\right]}{TLA_i} * 100$$

In the equation: UEIit addresses the yearly mean expansion intensity of i-th spatial zone during the time period t; ULAi,a and ULAi,b address the start and end developed area of i-th spatial zone. TLAi addresses the absolute land area of i-th spatial zone.

Models for Mapping Urban Growth

Markov Model

Markov model is an expedient technique for projecting LU/LC change when changes and forms in the scene are inflexible to construe. A Markov procedure is one in which the future condition of a framework can be recreated absolutely based on the right away going before state. Markov model will portray LU/LC change starting with one period then onto the next and use this as the basis to broaden future changes. These dynamics were achieved by developing a transition probability matrix of LULC changes from state one to state two, which displays the state of dynamic, while still serving as the source for modelling to a successive time period (Logsdon et al. 1996). Markov change detection technique is a simple procedure by which the state of transition could be scrutinize and analyse (Muller & Middleton 1994; Dongjie et al. 2008; Huang et al. 2008). The Markov change detection technique works by converting from state one to state two which is termed as transition of state. The expression used is as follows;

$$\boldsymbol{S(t+1)} = \boldsymbol{Pij} \times \boldsymbol{S(t)} \;\ldots\ldots.\; (1)$$

$$\boldsymbol{Pij} = \begin{pmatrix} \boldsymbol{P11} & \boldsymbol{P12} & \boldsymbol{P1n} \\ \boldsymbol{P21} & \boldsymbol{P22} & \boldsymbol{P2n} \\ \boldsymbol{Pn1} & \boldsymbol{Pn2} & \boldsymbol{Pnn} \end{pmatrix} \;\ldots\ldots\; (2)$$

$$(\boldsymbol{0} \le \boldsymbol{Pij} \le \boldsymbol{1} \quad \textit{and} \quad \sum_{j=1}^{N} \mathrm{Pij} = 1, (\boldsymbol{i}, \boldsymbol{j} = \boldsymbol{1}, \boldsymbol{2} \ldots \boldsymbol{n}) \;\ldots\ldots\; (3)$$

Where S(t) = State at time t, S(t+1) = State at time (t+1) Pij = Transition Probability Matrix
in a state.

Cellular Automata Markov Model

One congenital issue with Markov is that it gives no concern to the topography. This short coming is mitigated by combining the Markov model with a more dynamic and empirical cellular automata (CA) model and commonly referred to as the CA–Markov model. The cellular automata model incorporates the spatial dimension and thus adds modelling direction. Thus, the CA–Markov model has the advantage of predicting two-way transitions among the available land use types and is proven to have outperformed regression-based models in predicting land use change. CA filter is used to generate a spatial explicit contiguity-weighting factor to change the state of cells based on its neighbours. The filter used is a 5 × 5 contiguity filter. (Wang et al., 2020)

Artificial Neural Network

Artificial Neural network (ANN) models are information-based models. ANNs are integral assets that utilization a machine learning approach to measure and model complex pattern and characteristics and ANN modelling is worried about the extraction of models from mathematical information addressing the social elements of a framework. ANN has the extraordinary capacity of dealing with imprecise data by training. Artificial Neural network (ANN) is one of the meta-heuristic and information base models. Artificial Neural network structure can manage imprecise data and poorly characterized exercises. This assignment is completed by a process of learning from samples introduced to the ANN. Artificial Neural network due to the plausibility of learning, is a proper apparatus for ecological displaying. This strategy has been utilized in land use change modelling. These networks are made out of input layer, middle layers and an output layer. This kind of networks is utilized to distinguish nonlinear connections as more viable issues looked by non-linear peculiarities. (Mohammady et al., 2014)

The Analytical Hierarchy Process (AHP)

The Analytical Hierarchy Process (AHP) is a Multi Criteria Evaluation (MCE) which standardizes and calibrates the various selected factors and constraints, to generate a series of suitability maps for the Built-up area. The model works by rescaling the factors criteria (elevation, slope, proximity to road and proximity to urban areas) between 0 to 255, where 0 signifies less suitable and 255 signifies the most suitable and constraints were expressed in Boolean form 0 and 1, 0 coded as the excluded areas for built-up growth and 1 as the possible areas. Moreover, the model computes the weight of each selected factor criteria based on the importance of each factor in triggering the growth of built-up. The Analytical Hierarchy Process (AHP) was applied to determine the weight of each driving factor based on their percent of influence. The AHP model works by creating a comparison matrix of factors criteria involved in influencing urban growth. The key advantage of employing this model is, regardless of number of factors, the AHP requires only a pair of factors to compare at any given time (Omar et al. 2014; Keshtkar and Voigt 2015).

SUSM Model

A scenario-based urban growth simulation model (Kantakumar et al., 2019) SUSM utilizes remote sensing inferred inputs, for example, land use maps, incline, streets and focuses of metropolitan regions alongside metropolitan improvement situations. It involves logistic regression for adjustment and a compelled stochastic cell robot for re-enactment of metropolitan development. SUSM is tried in one of the quickest developing metropolitan agglomerations of India: The Pune city, which covers an area of 1642 km2. SUSM is equipped for anticipating the area of future urbanization with an exactness of 79% and a kappa index of agreement 0.81

SLEUTH model

The SLEUTH model is cellular automata-based computer simulation model that utilizes historical land use/ land cover (LULC), slope, road, and hill shade information to calibrate and simulate the land use/land cover change and urban growth. In addition to historical LULC information, the model uses five development factors (dispersion, breed, spread, slant safe and street gravity) and four development rules (diffusive, natural, edge and street impacted development). Some key characteristics of SLEUTH that make it promising as compared to the other urban growth models are; it requires less data relatively, incorporates CA which is able to imitate complex urban phenomena and having Geographic Information System (GIS) compatible environment. In spite the successes of SLEUTH in developing countries, it lacks in detecting the fragmented growth and small size built forms (Saxena & Jat, 2019).

FLUS model

The FLUS model has been successfully applied to the simulation of complex land-use and land-cover changes in China and on a global scale for modelling the dynamics of land cover changes for various human-related and natural environment driving forces. The FLUS model is implemented by training an ANN model to obtain an urban probability-of-occurrence (PoO) surface and by using a spatial simulation process that is based on a CA model. A roulette mechanism is designed to model the competition between urban land and nonurban land in each cell, which make the FLUS model more capable of capturing the uncertainty and randomness of urban development (Liang et al., 2018)

CART model

The CART model is a typical data-driven model used to extract transition rules CART is a rule-based model, and each rule denotes an ‘If-Then’ definition of the relationship between urban development and relevant proximity variables with a continuous probability. The obtained transition rules derived from varying proportions using two methods: threshold-based comparison (i.e. OA) and ROC value (Yao et al., 2017)

CONCLUSION

Sophisticated geo-visualisation of growth in urbanisation would aid in decision making towards cities to be sustainable with minimal amenities and infrastructure. Remote sensing and GIS coupled with temporal dataset can be of immense helps in mapping and understanding of urban dynamics. The basic Land cover and land use classification when analyzed through mathematical model such as Shannon's Entropy, aids in measuring the spread and pattern of urbanization over the years. The increasing population over the Indian Himalayan Region increases the impact of artificial structure over the natural cover of the region thus fragmenting the landscape and damaging the ecological and biological condition of the region. Thus measuring the landscape fragmentation over the years is of great analyzes to understand the trend of ongoing urbanization. Delineation of parameters that are most likely to influence the land use of the area has advanced the level of prediction accuracy. The simulation of Built-up changes through Cellular Automata Markov Model and Artificial Neural Network (ANN) suggests a consistent increase of urban areas with a reduction in the natural vegetation cover in the region. Addition of Analytical Hierarchal Process and Fuzzy decision to the model has facilitated assimilation of man's decision for tackle spatial issues.

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