Spatial modelling of urban change using satellite remote sensing: a review

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Abstract: Urbanization is one of the most evident human-induced global changes. Population growth is an important factor that contributes to change in any urban system. Although urbanization has been an issue of concern, its rate is of a more serious concern. Despite its economic importance, urban growth has a considerable impact on the surrounding environment. Addressing the various challenges posed by urbanization process requires spatio-temporal analysis of cities and regions. This is because cities are dynamic so also are the processes that are shaping cities globally and locally. Researchers and city planners have assessed urbanization processes through the lens of remote sensing and Geographic Information System (GIS). Recent advances in RS and GIS tools with varying analysis techniques have enabled researchers to model urban change effectively. Using a critical review approach, this paper contributes to the growing bodies of knowledge by reviewing published studies that made use of satellite RS and GIS in understanding the dynamism of urban areas through change detection and urban modelling.

Introduction

Urban areas are regions with a high level of spatial dynamism where their size is rapidly increasing. Urbanization is one of the most evident human-induced global changes worldwide. In South Africa, urbanisation levels reached 56% in 2001, resulting in a 4.3% increase from 1996 to 2001 (Kok and Collinson, 2006). The growth of urban areas depends on numerous factors including social, economic, demographic, environmental, geographic, cultural, and others. Therefore, modelling such a dynamic system is a challenging task.

Population growth is one of the most important factors that contribute to any urban system change. The expansion of a city beyond its periphery requires population growth spatially distributed. Growth in population contributes to urban change by absolute growth, which increases urban areas, and changes the dynamics of urban demography. Of that urban population, the numbers residing in small cities generally swells at a striking rate, and in parallel, there is usually an associated decrease in household sizes and a related increase in the number of housing units (Qiu, *et al.,* 2003).

Remote sensing (RS) and Geographic Information Systems (GIS) techniques are some geospatial tools being widely used to assess natural resources and monitor spatial changes. Land use/cover (LULC) change dynamics can be analysed using time series remotely sensed data and linking it with socio-economic or biophysical data in GIS (Moeller, 2004). The incorporation of RS and GIS enables unique analyses involving environmental changes and these include land cover mapping, detecting and monitoring over time, identifying land use attributes, and change hot spots. With the advancement of technology, reduction in data cost, availability of historic spatio-temporal data and high resolution satellite images, GIS and RS techniques are now useful research tools in spatial change and modelling (Feng, 2009). This review focuses on published studies that have been conducted using satellite remote sensing data in urban change detection and modelling. In addition, the paper considers the cellular automata and Markov models used in urban growth.

Urban growth and sprawl

Urban growth varies in definition across countries and fields of studies. It shall be considered for this review as the increasing physical transformation of urban land into other structures such as buildings in response to population increases. It could be planned or unplanned. This review focuses on the unplanned growth, also referred to as sprawl.

Urban sprawl refers to uncontrollable, irresponsible and poorly planned expansion of an urban area into rural land destroying green spaces, increasing traffic, contributing to air pollution, leading to congestion with crowding and does not contribute significantly to national income. The direct implication of urban sprawl is change in land-use and land-cover of the region since sprawl induces an increase in built-up and paved areas (Bhatta, 2012; Mohammadi, *et al.,* 2012). Urban sprawl can be considered a significant and growing problem that entails a wide range of social and environmental issues (Araya and Cabral, 2010).

Researchers have been challenged with the definition of urban sprawl as it can be considered from different perspectives. According to Bhatta (2012) sprawl may either refer to: certain patterns of land use, or processes of land development, or causes of particular land-use behaviours, or consequences of land-use behaviours.

Urban sprawl can be measured through the use of indicators selected according to the specific area of study. These indicators include low-density or single-use housing; development at substantial distance from urban areas; development in radial, stripped or isolated emanating from urban areas; development into protected or agricultural land; and others. Researchers have established multi-dimensional indicators through GIS analysis or descriptive statistical analysis to measure urban sprawl (Fina and Siedentop, 2008; Schneider and Woodcock, 2008). RS and GIS can be applied separately or in combination for application in studies of urban sprawl (Wei, *et al.,* 2006; Huang, *et al.,* 2007; Yu and Ng, 2007; Mahesh, *et al.,* 2008).

Understanding the geographic locations of urban growth points is an essential aspect in urban studies. Researchers require monitoring systems to enable them spatially locate initial seed points and the development type resulting from them. These systems can be used for planning purposes and a detailed reporting of overall urban growth. They include geospatial tools which can enable the comparison of different cities by their growth levels (Moeller, 2004).

Urban change detection and modelling

Urban change detection involves the identification of missing regions in one image corresponding to appearance or disappearance of objects, motion of objects or shape changes of objects in an urban environment and surroundings. This change has traditionally been detected by defining a threshold. The threshold can be chosen empirically as in specific applications or commonly-used automatic thresholding methods classified into two bases: gray-level distribution and spatial properties (Rosin, 2002). A review of image difference followed by threshold-based method has been proposed (Radke, *et al.,* 2005).

A spatial data analysis method that comprises exploratory data analysis and spatial logistic regression technique is used to seek and model major determinants of urban growth of Wuhan City in China (Cheng and Masser, 2003). In identifying spatio-temporal trends and dimension of urban form in Dhaka metropolitan area, Landsat images were classified using index-based expert process (Basak, 2006). The study was further modified by including socio-economic data for the evaluation (Dewan and Yamaguchi, 2009). A supervised classification algorithm and the post-classification change detection technique in GIS were applied. The accuracy of the land cover maps ranged from 85% to 90%.

Remote sensing techniques have also been used to quantify and map the detected changes in urban areas. Landsat Thematic Mapper (TM) imagery was used to quantify forest cover change in the Sundarbans of Bangladesh from 1989 to 2000 (Emch and Peterson, 2006). They applied the Normalized Differential Vegetation Index (NDVI), maximum likelihood classification and sub-pixel classification image processing techniques. While Griffiths, *et al*. (2010) on their part mapped the urban growth of Dhaka megacity region (1990 to 2006) using multi-sensoral data. They used a Support Vector Machine (SVM) classifier and post-classification comparison to reveal spatio-temporal patterns of urban LULC changes.

Predictive models have been developed that exploit the relationships between nearby pixels both in space and time (when an image sequence is available); and methods that are based on the fact that the decision rule is casted into a statistical hypothesis test (Araya and Cabral, 2010). Remotely sensed information is very useful in describing and modelling urban development process.

The predictive power of models such as the Cellular Automata (CA) based approach has been successfully validated for urban land use change (Araya and Cabral, 2010; Tewolde and Cabral, 2011). Cabral and Zamyatin (2006) implemented three land change models to forecast the urban dynamics in Sintra-Cascais municipalities of Portugal, for 2025. The models are CA-Markov chain model (CA-Markov), CA-Advanced and Geomod. The authors used image segmentation and texturing procedures to classify the Landsat images of 1989, 1994 and 2001. In predicting the urban growth of Sydney, Lahti (2008) used the CA model Metronamica, developed by the Research Institute for Knowledge Systems in the Netherlands. Wang and Mountrakis (2011) developed a GIS-based modelling framework called Multi-Network Urbanization (MuNU) model, which integrates multiple neural networks, to predict growth as in Denver Metropolitan Area.

An integrated Artificial Neural Networks and CA (ANN-CA model), was introduced for simulating the land-use map (Li and Yeh, 2000). The proposed model was implemented in China using satellite images. SLEUTH urban growth model is necessary to simulate the historical growth pattern of an area. SLEUTH model incorporates Slope, Landuse, Exclusion layer (where growth cannot occur), Urban, Transportation and Hill-shade data layers. SLEUTH uses a modified CA to model the spread of urbanization (Kashem, 2008). The integration of satellite RS and GIS can be an effective approach for analysing the spatio-temporal patterns of LULC change (Mubea, *et al.,* 2010). They combined satellite RS, GIS and Markov chains stochastic modelling techniques to analyse and project LULC changes. The results indicated that there has been a notable and uneven urban growth with substantial forest loss.

Remotely sensed data for change detection

Remote sensing is characterized by spatial, temporal, and spectral heterogeneity of urban environments (Herold, *et al.,* 2002). It is irrefutably a modern science, which studies the earth's changing environment, through remote sensing tools such as satellite imagery and aerial photographs. It is an appropriate source of urban data to support studies of urban growth as it provides a unique perspective on growth and land-use change processes (Lillesand, *et al.,* 2008).

Effective analysis and monitoring of land cover changes require a substantial amount of data about the Earth's surface. This is most widely achieved by using remote sensing tools. Remote sensing provides an excellent source of data, from which updated LULC information and changes can be extracted, analysed, and simulated efficiently. LULC mapping, derived from remotely sensed data, has long been an area of focus for various researchers (Herold, *et al.,* 2002; Yuan, *et al.,* 2005; Oluseyi, 2006; Mubea, *et al.,* 2010). Monitoring these changes and planning urban development can be successfully achieved using multi-temporal remotely sensed data, spatial metrics, and modelling (Araya and Cabral, 2010).

Remote sensing data derived from satellite sensors such as Landsat can provide information about the areal extent, conditions, boundary and monitoring of urban changes. Recent studies make use of data from different sensors to measure changes in landmass and population size. Ade and Afolabi (2013) used TM, ETM+ and Nigeriasat 1 data to analyse the physical expansion of Jos city. Importantly, remotely sensed imagery provides an efficient means of obtaining information on temporal trends and spatial distribution needed for understanding, modelling, and projecting land change (Epstein, *et al.,* 2002). It is consistent over great areas, time, and can provide information at different geographic scales.

Remote sensing analysis and modelling of urban change

Understanding the urban patterns, dynamic processes, and their relationships is a primary objective in the urban research agenda with a wide consensus among scientists, resource managers, and planners, because future development and management of urban areas require detailed information about ongoing processes and patterns. These patterns can be systematically mapped, monitored and accurately assessed from satellite data along with conventional ground data. RS and GIS techniques may be used as efficient tools to detect, assess and map land use changes (Araya and Cabral, 2010). In order to detect and evaluate urban changes, Reveshty (2011) applied image differencing, principal component analyses as well as fuzzy ARTMAP for classification. Results for the different dates are compared which reveal significant changes. For predictions into future scenarios, the combined CA with Markov chain analysis was employed.

The built-up area in an urban setting is generally considered as the parameter of quantifying urban sprawl (Epstein, *et al.,* 2002). It is quantified by considering the impervious or the built-up as the key feature of sprawl, which is delineated using toposheets or through the data acquired remotely. Mohammadi, *et al.* (2012) used Shannon's entropy, which reflects the concentration of dispersion of spatial variable in a specified area, to measure and differentiate types of sprawl. The measurement is based on the notion that landscape entropy or disorganisation increases with sprawl.

The spatial phenomenon in urban growth modelling is simulated geometrically using techniques of CA. The CA technique is used extensively in urban growth models and simulation. The challenge 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 highway. Cheng and Masser (2003) modelled the urban growth pattern for Wuhan city in China considering the causal factors. This method was challenged in not being able to spatially pinpoint accurately where sprawl could occur. This challenge could be addressed by applying neural network to remotely sensed data especially for classification and thematic representation (Wang and Mountrakis, 2011).

Cellular Automata

Urban growth modelling is getting more attention as an emerging research area in many disciplines. This is because of the recent dramatic increase in urban population that has increased pressure on infrastructure services (Batty, 2005). In recent years, there has been a prolific application of CA models to urban systems. The models are impressive in terms of their technological evolution in connection to urban applications (Yang and Lo, 2003).

CA enables the understanding of the urbanization phenomenon and the exploration of what-if scenarios. It constitutes a possible approach to urban growth modelling by simulating spatial processes as discrete and dynamic systems in space and time that operate on a uniform grid-based space (Araya and Cabral, 2010). The ability of CA to represent complex systems with spatio-temporal behaviour, from a small set of simple rules and states, makes it suitable for modelling and investigating urban environments (Tewolde and Cabral, 2011).

CA simplifies the simulation of complex systems wherein basic elements of the city are represented in two distinct but related ways: through cells which represent the physical and spatial structure of the city, and through agents, which represent the human and social units that make the city work (Cabral and Zamyatin, 2006). CA models are attractive for simulating urban systems since local action gives rise to global forms emerging spontaneously with no hidden directives for the macrostructures. CA algorithm offers an interesting and innovative approach for simulation of urban systems.

Markov Model of Change Detection

The Markov model is an application that can be used to predict future changes based on the rates of past change. It is based on the probability that a given piece of land will change from one mutually exclusive state to another (Wijanarto, 2006). It functions by creating a transition matrix of pixels in each class for two time periods – basically the same as the cross-tabulation matrix that is used for accuracy assessment. The main diagonal of the matrix contains pixels that have not changed, while other cells contain pixels that have changed. In order to generate probabilities of change between classes, each cell value is divided by its row total. This results in the probability that a given class in date 1 will convert to another class in date 2 out of all possible changes (Lillesand, *et al.,* 2008).

Therefore, the Markov model analyses a pair of land cover images and outputs a transition probability matrix, a transition area matrix, and conditional probability images. The transition probability matrix shows the probability that one land -use class will change to the others. The transition area matrix tells the number of pixels that are expected to change from one class to the others over the specified period. The conditional probability images illustrate the probability that each land cover type would be found after a specific time passes (Reveshty, 2011). The number of possible states is either definite or denumerable and for LULC, the states of the system are defined as the amount of land occupied by various LULC (Mubea, *et al.,* 2010).

A Markov model applies contiguity rule like a pixel near to an urban area is most likely to be changed into urban area. The Markov and CA models can also be used in combination to predict land cover change (Reveshty, 2011; Ahmed and Ahmed 2012). In applying the following models: Stochastic Markov, CA-Markov and Multi-Layer Perceptron Markov, Ahmed and Ahmed (2012), chose the latter as best-fitted model to make a single land cover map for future prediction which aggregates all the Markovian conditional probability images. This prediction is performed by a stochastic choice decision model. In order to regularise and detect irregularities in images such as noise a patch-wise Markov random field framework is applied as opposed to the pixel-wise model.

Conclusion

Urban growth is an unstoppable process in development which can only be managed through proper planning. The planning process can only start by identifying the growth points within urban areas. Satellite remotely sensed data has proven essential in this identification and mapping process of such growth.

Numerous works have shown that satellite remote sensing has the potential to provide accurate and timely geospatial information describing urban changes. Although LULC changes have in the past been monitored by traditional inventories and surveys, satellite remote sensing can be more effective as it can provide greater amounts of information along with advantages of cost and time savings for extensive areas.

Advances in satellite-based land surface mapping are contributing to the creation of considerably more detailed urban maps, offering planners better understanding of urban growth dynamics and sprawl. Recently, the implementations of these techniques to quantify, analyse, and model the urban growth dynamics has been successful as illustrated by this review. Therefore being useful to town and regional planners.

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