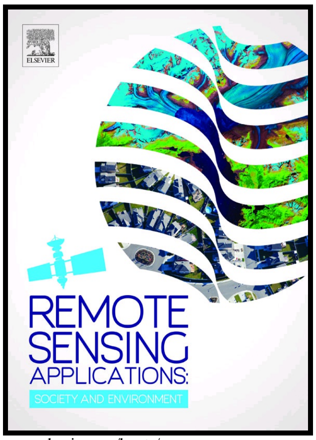


www.elsevier.com/locate/rsase

Application of Cellular automata and Markov-chain model in geospatial environmental modeling- A review

Pramit Ghosh, Anirban Mukhopadhyay, Abhra Chanda, Parimal Mondal, Anirban Akhand, Sandip Mukherjee, S.K. Nayak, Subhajit Ghosh, Debasish Mitra, Tuhin Ghosh, Sugata Hazra

PII: S2352-9385(16)30025-8
DOI: http://dx.doi.org/10.1016/j.rsase.2017.01.005
Reference: RSASE53

To appear in: *Remote Sensing Applications: Society and Environment*

Received date: 16 April 2016
Revised date: 4 October 2016
Accepted date: 18 January 2017

Cite this article as: Pramit Ghosh, Anirban Mukhopadhyay, Abhra Chanda Parimal Mondal, Anirban Akhand, Sandip Mukherjee, S.K. Nayak, Subhaji Ghosh, Debasish Mitra, Tuhin Ghosh and Sugata Hazra, Application of Cellula automata and Markov-chain model in geospatial environmental modeling- A review, *Remote Sensing Applications: Society and Environmen* http://dx.doi.org/10.1016/j.rsase.2017.01.005

Application of Cellular automata and Markov-chain model in geospatial environmental modeling- A review

Pramit Ghosh[1], Anirban Mukhopadhyay[1*], Abhra Chanda[1], Parimal Mondal[1], Anirban Akhand[1], Sandip Mukherjee[1], S.K. Nayak[2], Subhajit Ghosh[1], Debasish Mitra[3], Tuhin Ghosh[1], Sugata Hazra[1]

[1]School of Oceanographic studies, Jadavpur University, Kolkata, India

[2]Geological Survey of India, CHQ, Kolkata, India

[3]Indian Institute of Remote Sensing, Dehradun, India

[*]Corresponding Author: School of Oceanographic studies, Jadavpur University, 188 Raja SCM Road, Kolkata-700032, India. Tel.: +91 9831432302. anirban_iirs@yahoo.com

Abstract

Cellular Automata (CA) & Markov-Chain modeling are concepts that are utilized in numerous branches of science. Powerful as they are independently, these two theoretical concepts can be of immense use when fused together and applied in practical situations. CA and Markov models have spread their wraths over geosciences and with the advancement of remote sensing and GIS technologies along with an exponential increase in computing and modeling power. Over the last few years, these concepts have found a solid ground for research in this domain of geospatial environmental modeling in earth sciences. It is widely used to characterize the dynamics of land use/cover, forest cover, urban sprawl, wetland landscape, plant growth and modeling of watershed management, suitable site selection, coastal zone management and so forth. This paper aims to categorize these researches into broad categories. This paper discusses the concepts of CA-Markov modeling and their backgrounds and is followed by a classification of the researches conducted in this domain into two broad groups, one being the development of concepts and the adopted methodologies, while the other discusses the application of these methods in solving and studying real world scenarios. Recent developments in this domain have been observed which uses concepts and technologies previously unused in conjunction to CA. However, several limitations like non-accountability of human influences, unavailability of high resolution imagery, primary discrepancy between the simulations of CA with GIS, human decision making were also addressed in details. At the same time numerous advancements like inclusion of fuzzy logic, possibility of textural classification, removing biases in simulation and developing a CA-based 2D and 3D land use simulation module are elaborated which are at present showing some promising avenues wherein significant research can be done in future.

Keywords: Cellular Automata, Markov-Chain model, remote sensing and GIS, environmental modeling

Introduction:

Any research or study dealing with the real world scenario is very difficult to accomplish owing to the diversity and several types of constraints inbred within a natural system. In the last few decades, the emergence of the field of remote sensing has led to the discovery of several avenues of research like characterizing land use land cover change of a natural ecosystem, analyzing geomorphological change dynamics of various land forms and so forth. In addition to the utility that remotely sensed images has provided to the researchers and scientists in the field of environment, geography, and geology etc. several developments also took place in the field of mathematical modeling. The mathematical and statistical advancement further aids the analysis in these kinds of studies. Two such important sectors are the Cellular Automata (CA) and Markov chain analysis.

Development of Cellular Automation (CA) systems is attributed to Stanislaw Ulam and John von Neumann working at Los Alamos laboratory in New Mexico (Shiffman, “The Nature of Code” - http://natureofcode.com/). While Ulam was studying the growth of crystals, von Neumann was imagining a world of self-replicating robots – structures or patterns which can build copies of it over time. This is the core philosophy of CA, similar to the process of biological evolution, where patterns replicate themselves on a grid by following some simple rules. British mathematician, J.H. Conway, in 1970, devised a game based on CA known as "Conway's Game of Life" or simply "Life". Subsequently popularized by Martin Gardner in his "Mathematical Games" column in Scientific American, Conway's Game of Life made its first appearance to the general public in October, 1970 (Scientific American, 223, pages: 120-123). This was instantly famous and as Gardner writes, "it also opened up a whole new field of mathematical research, the field of cellular automata ... Because of Life's analogies with the rise, fall and alterations of a society of living organisms; it belongs to a growing class of what are called simulation games". The concept of CA has potential to be applied in various branches of science as thoroughly documented by Stephen Wolfram in his book, "A New Kind of Science" in 2002.

Cellular Automata is, in general, a collection of cells, of an arbitrary shape, arranged in a grid-like structure. These cells can "hold" different values from time to time - binary being the simplest of the forms. All the cells change their states simultaneously, i.e., at the same time according to some rule - which may be fixed at the beginning or may vary from time to time. These rules are applied on the system at a regular discrete time interval. These rules lead to a new state for each cell which may or may not be the same as its previous state. These rules consider the states of the cells in a neighborhood - usually a pre-defined list of adjacent cells to the cell under consideration. There is a rule for every possible combination of states in the cell's neighborhood.

A Markov chain on the other hand is a random process having a property characterized by memoryless-ness - i.e., transition from one state to another on a state space take place such that it depends only on the present state and not on the past states that the process went through. A random process could be termed as a Markov chain when in a series of events, any event that is about to occur depends only on the present state and eventually forms a kind of a chain. Although any number of events occurring independently one after another satisfies the formal definition of a Markov chain trivially, the theory gains appreciation when the next state depends on the current state as a probability.

In the last two decades, CA and Markov modeling has gained widespread popularity in the geographic and spatial domains. Among these studies, land use classification and urban growth modeling are some phenomenon where implementation of CA and/or Markov chains has given sufficiently accurate results. Remotely sensed imagery of land, usually space-borne, can be classified into discrete areas of land use - with each type of land use / land cover being a state in the state space of the CA model. The pixels can be thought of as the cells in the grid. The change of a patch of land, from one use to another can then be modeled as a transition, with the probability being defined by various factors - spatial or in some cases non-spatial factors like socio-economic ones according to the objective of the study. The Markov chain can be applied to simulate the use / cover of a piece of land with transition being carried out in discrete time steps amounting from some months to a year. A GIS can be integrated to this whole system to predict the future scenario of land use / land cover of the area under observation.

A number of factors usually influence the pattern of land use / cover change in the real world. The selection of spatial and non-spatial factors is dependent on the objectives of the study. In most of the occasions, the factors that are considered depend on the easy availability of data for the selected region of study. The location of the study area also influences the selection of spatial and non-spatial factors which are to be used as parameters in the study. For example, if the study area is located in a hilly area with frequent changes in elevation, then the Digital Elevation Model (DEM) map of the region will highly influence LULCC of the region. Slope and aspect will be the spatial factors that would probably be included for a study in such an area. Similarly, if the study area is in a rural region, then the socio-economic factors could play an important role as a non-spatial parameter for the study. Again, while considering a strategically sensitive area like international borders, easy availability of high-resolution spatial data, such as Hyperspectral data, may be a difficult affair and in that case they would not be included for the study. Road networks and river positions could also play an important role while analysing LULCC of a region – especially in an urban area. Proper drainage maps and proximity to major roads are expected to be included in case of urban area related studies.

In this paper we have observed the relevant works and studies done in this area and have tried to classify the developments and advancements into a categorical form based on their objective. The works have been broadly divided into those which have tried developing or modifying new methodologies and algorithms and those which have applied these already developed or developing algorithms to a real world or, in some cases, hypothetical scenarios with an experimental outlook. Emphases have been given on recent works in this domain and have highlighted the current trends in research in this field using CA and/or Markov modeling.

Brief Descriptions of methodologies:

Markov Chain Modelling for future predictions:

A Markov chain model is a stochastic process which analyses the probability that one state will change to another one – i.e., the state of a system at time t_2 is predicted from the state the system is in at time t_1 (Thomas & Laurence, 2006).

Future prediction using Markov chain modelling is generally done by analysing two qualitative land cover images taken on different dates (Moghadam & Helbich, 2013). Three objects are produced as a result of this analysis. The transition probability matrix stores the probability that each state will change to every other state. The transition area matrix, produced from this transition probability matrix (Mousivand et al., 2007), stores the expected number of pixels that might change over a predetermined number of time units (Behera et al., 2012). The conditional probability images produced (Guan et al., 2011; Tang et al., 2007) express the probability that each pixel will belong to the designated class in the next time step. In Markov chain model, land cover change is thought of as a stochastic process. The state at a particular time *t* is dependent exclusively on the state at previous time step *t-1* and not on the states before that – i.e., at times *t-2*, *t-3* and so on. The transition probability equation can be written as,

$$P\{X_t = a_i | X_0 = a_0, X_1 = a_1, \dots, X_{t-1} = a_i\} = P\{X_t = a_i | X_{t-1} = a_i\}$$

With the change process being uniquely distinct with time (t = 0, 1, 2 …)

In the above equation, the term $P\{X_t = a_j \mid X_{t-1} = a_i\}$, is the single-step transition probability of the transition from state a_i to a_j in a single time step. If *l* steps are necessary for implementing this transition, then this term is called the l step transition probability, abbreviated as $P_{ij}^{(l)}$. A Markov chain is said to be homogeneous if $P_{ij}^{(l)}$ depends only on the states a_i, a_j and l. Thus writing $P\{X_t = a_i | X_{t-1} = a_i\}$ as P_{ij}, we have:

$$P\{X_t = a_i | X_{t-1} = a_i\} = P_{ij}$$

Here, the term on the right hand side is derived from the observed data by counting the number of times the state changes from i to j (n_{ij}) and the number of occurrences of the state a_j. Thus from the above equation,

$$P_{ij} = \frac{n_{ij}}{n_i}$$

As the Markov chain develops, the pixel's probability to remain in the state j gradually becomes independent of the initial state of the chain. When this is achieved, the chain is said to have attained a steady state and for the determination of $P_{ij}^{(l)}$, the limiting probability P_j is applied according to the equation:

$$\lim_l P_{ij}^{(l)} = P_j,$$

where j = 1, 2, 3… (state); $P_i = 1$; $P_j > 0$

For transition probability matrix, each element consist of a category with the observed and expected number of transitions as per the equation,

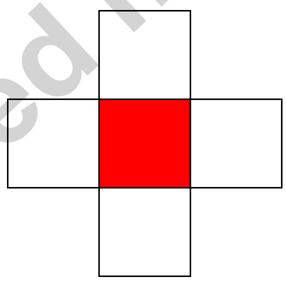
$$\chi = \sum \frac{(O-E)^2}{E},$$

where O is the observed number of transitions and E is the expected number of transitions. In each case, the successive states are independent.

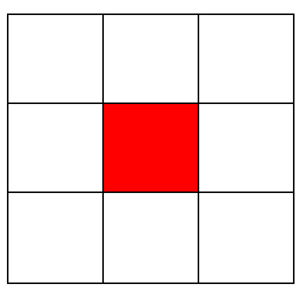
Cellular Automata

From the principle of operation of Markov chain, it is evident that it is independent of the states of the cells neighbouring the cell under observation (Eastman, 2006). Thus, Markov modelling alone is not sufficient for analysing the problem simply because it does not consider the spatial distribution of each category. Hence, even though, it can correctly predict the magnitude of change, the right direction cannot be obtained (Boerner et al., 1996). Thus, cellular automata model is implemented to take into account the spatial nature and hence the direction of the data (Soe & Le, 2006). Proximity is a very important geospatial element governing the change events (Arsanjani et al., 2013). In cellular automaton, the state changes not only depend on its previous state but also on the state of the cells immediately neighbouring the cell in question (Clarke & Gaydos, 1998). All the locally defined transition rules decide the overall performance of the system.

Cellular automaton is composed of five elements. (1) Cell space is the space under a single particular cell. (2) Cell state is the representation of some spatial variable under observation, (3) time steps are the discrete steps of time over which the automaton evolves, (4) transition rules are the functions which determine the change of the state of each cell taking into consideration its own and its neighbouring cell's states and (5) neighbourhood – the spatial distribution of the cells which will be considered when applying the transition rules. Two very commonly used 2-dimensional (2D) neighbourhoods are the Moore neighbourhood and the von Neumann neighbourhood as shown below:



(a) Von Neumann neighbourhood

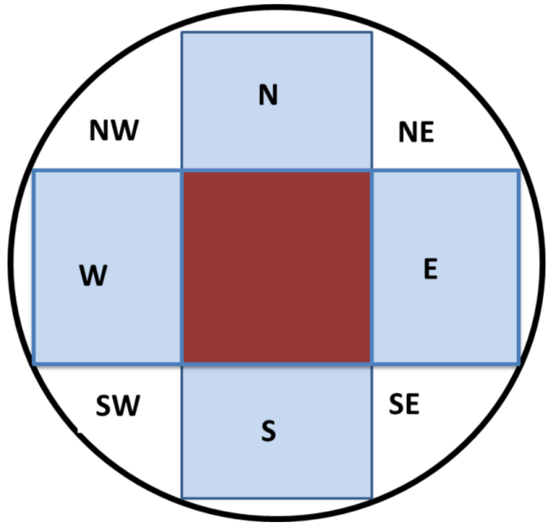


(b) Moore neighbourhood

Moore neighbourhood has been found to result in an exponential growth rate when modelling urban areas, which pose a problem as it does not reflect the actual growth pattern. In such cases, the von Neumann neighbourhood is usually used to model a slower and controlled rate of growth (Yeh & Li, 2006). In a number of publications (Kocabas & Dragicevic, 2006; Li & Yeh, 2010), different kinds of neighbourhoods have also been experimented with. According to Kocabas & Dragicevic (2006), though rectangular and circular neighbourhoods give almost the same effect for small sizes, the difference in the results gets pronounced when the cell size is increased. Li & Yeh (2010), however, has argued that since a circular neighbourhood has no bias towards any particular direction, therefore, it gives a better result. This biasness has been diagrammatically shown in the figure below. Distortions may be produced in simulations based on rectangular neighbourhoods, namely, von Neumann & Moore neighbourhoods, which are said to be absent in those using a circular neighbourhood for the automation (Li & Yeh, 2010).

It is to be noted, however, the term ‘cells’ is only an abstract terminology – i.e., they are necessarily not adjacent. Strict CA is a special type of Cellular Automata which work with the neighbourhood defined as the nearest neighbours, giving them a property of “emergence”. They act locally, but give rise to a kind of a global pattern. Cell-space models may waive this limitation.

These symmetric patterns generated by CA are highly suitable for LULC change modelling.



Von Neumann neighbourhood inscribed inside a circular neighbourhood. It can be easily seen that for the same cell coloured red, the neighbourhood located in the North, West, South and East directions (coloured blue) have been given more weight than the regions North-West, South-West, South-East and North-East in case of the rectangular von Neumann neighbourhood. On the other hand, all of these areas have been given the same priority.

By the fusion of Markov chain modelling with CA the spatial and temporal attributes can be perceived. The CA model, alone, provides a powerful technique for computing that can be used to simulate spatial variation of a system (Kamusoko et al., 2009). The CA-Markov model on the other hand can be used to achieve better simulation for temporal as well as spatial patterns of land class changes (Sang et al., 2011).

Broad classification of work:

Most of the literature available in the field of CA and/or Markov chain analysis in the geospatial domain can be broadly classified into two groups – one being those which discuss various methodologies and their adaptations and variations, and another being the application of these methodologies in the real or sometimes, hypothetical world. First of all, each and every category is classified according their domains of applications in a tree-like diagram and the content of their works is discussed in details. Next, we note the latest developments in this field under a separate heading and discuss the current trends and topics in which research has been done in the recent past. Finally, we discuss the limitations and the future scope of some selected works to point out which areas need more attention in developing this domain of application of CA and Markov chains.

Development of methods – their adaptations and variations

Much of research has been done on the methodologies employed in using Cellular automata in the geospatial domain (Fig. 1). New algorithms have been developed; existing methods have been adapted to suit a particular phenomenon in nature or experimented on different domains of application. Integration of CA and GIS remains a very important part of land development studies. Wagner (1997) has identified some problems in contemporary GIS like performance of operators and the efficiencies of handling spatiotemporal dimensions. He has identified the similarities between GIS and CA, and has tried to implement the functions of GIS with CA and vice-versa. Along with this, the feasibility of using a CA machine as the analytical workhorse of GIS has also been studied. Ways to extend CA and integrate it with GIS has been discussed by Yeh & Li (2001). The concept of gray cell to reflect the degrees of urban land development has been used to provide better results. We see that integration of CA and GIS in the mid-1990s paved the way for more coupling of such similar subjects and welcomed the cellular automata in the geospatial domain.

Advanced optimization techniques like Ant Colony Optimization (ACO) and Particle Swarm Optimization (PSO) have been used to improve various steps in the modeling process. Eventually, concepts of Geo-Algebra / Map Algebra have also found use in geospatial modeling. While integration of Markov chains remain a widely used methodology, relatively newer concepts like Data Mining and Artificial Neural Networks have also found their way to the geospatial domain. Alongside the integration of CA and GIS, at around the same time, Geo-algebra had been introduced, which proved to be a practical foundation of the theoretically oriented concept of cellular automata. Problems arising in the integration of the original CA framework with GIS make the model difficult to comprehend and implement. This problem has been addressed from a theoretical standpoint by Couclelis (1995) and an answer has been found in the form of proximal space. The practical counterpart was handled successfully using Geo-Algebra. In a paper by Takeyama & Couclelis (1997), the mathematical formalism of CA has been generalized within Geo-Algebra which is a mathematical generalization of Map Algebra. Map dynamics has been shown to support spatial database manipulations and modeling within GIS. The start of the new decade saw the integration of more computer science, mathematical and statistical topics with the geospatial domain - Data mining, artificial neural networks and

Markov chains to name a few. Li & Yeh (2001) has presented a new CA model which uses artificial neural networks for both calibration and simulation. The large number of variables and parameters used to model real cities are difficult to handle, but according to this new model these parameters for CA simulation are computed by the help of training of artificial neural networks. This omits the need for providing detailed transition rules which are difficult to define. The model has shown better accuracy than the classical CA models in simulating complex urban systems. Data mining technique has been applied to automatically reconstruct the transition rules of CA explicitly - which are more helpful to decision-makers. This model proposed by Li & Yeh (2004) can easily reduce uncertainties in defining transition rules and generate more reliable results. A new urban expansion dynamic (UED) model has been presented by He et al. (2008) to effectively capture the urban development process. Xin et al. (2012) has also proposed a spatiotemporal model of land use change based on Ant Colony Optimization (ACO), Markov chain and CA. The accuracy of this model was measured and it was found to be very useful for land use change simulation. When compared to other models like CA-Markov and ACO-CA, it was found, that this was more accurate in predicting the quality and distribution of land use change.

In order to overcome the problems of raster based and vector based CA models, a hybrid CA model has been developed by Rabbani et al. (2012) to incorporate the best of both the worlds. Particle Swarm optimization (PSO) has been used to calculate the probability of a cell to transform to an urban scenario based on the proximity to various development parameters. When compared to the ground truth data, it was found that the Kappa coefficient accuracy was 83.42%. In this decade, optimization techniques have also made their way to contribute to geo-scientific problems. Classification algorithms pertaining to CA have also seen developments. Contextual and hierarchical classification techniques have been used for pixel categorization.

Genetic algorithms have been used to automatically calibrate the classified image. Results achieved in adopting these methods show great improvements than classical and traditional techniques. Since the year 2007 till the present, automatic categorization of regions has popped out as an intriguing topic for research. Experimentation with transition rules and the use of genetic algorithms and fuzzy rules were seen in this period. A new algorithm was devised by Alkheder et al. (2006) to simulate historical growth based on local neighborhood structure of the input data. The paper uses genetic algorithms to propose an automatic rule calibration method. The results obtained had good accuracy in both short and long terms. A kernel based non-linear CA was used for simulating the complex urban developments by Liu et al. (2007). They have noted that a typical calibration procedure uses linear regression models like MCE where in the real world a non-linear approach would be preferable because of the immense complexity of urban growth. Linear transitional rules of the CA were considered insufficient in accurate modeling and the authors have, thus, proposed a new kernel based learning technique to acquire non-linear transition rules for CA. The proposed model was found to be mathematically transparent in comparison to models using neural networks making the results easier to handle and interpret. The model has been applied on a fast growing urban environment and the results were more accurate than the neural network based CA. Espinola et al. (2010) have focused on the need to improve classification algorithms. In spite of a number of pre-existing algorithms, a new Algorithm based on Cellular Automata (ACA) has been explored by the researchers. One of the aims of the study was to obtain a pseudo-fuzzy classification algorithm based on spectral proximity hierarchies in the feature space. It was found that this satellite image classifier algorithm gives better results than the classical ones. Validation and experimentation was done in the SOLERES framework. Though there exists various types of classification algorithms such as parallelepiped, minimum distance classifiers and others, performance of such algorithms need to be improved with respect to their accuracy rate. It was studied by Espinola et al. (2014) that CA can offer many advantages when combined with classical classification algorithms. An ACA has been developed by the authors which apart from improving classification accuracy rate with the help of contextual techniques, also offers a hierarchical classification of the pixels divided into the level at which it belongs to a class. Harikrishnan & Poongodi (2015) have also studied and implemented fuzzy rules with an aim of classifying satellite imagery. The accuracy rate of the classified image was also analyzed by them. Fuzzy logic has also been used along with CA. Gray cells concept has also been used in a number of occasions.

Attempts of total integration of fuzzy logic, cellular automata and GIS were done by quite a number of researchers. Gar-On Yeh et al. (2001) has identified that although CA urban models assume the development densities to be uniform for all cells, this is not so in case of real cities. In order to overcome this shortcoming, a CA model has been developed by the authors that take into account a density gradient extracted from density-decay functions. Based on the concept of gray cells, this model was found to be a useful tool to explore the variations in urban development densities. A fuzzy constrained cellular automata model of forest insect infestations by Bone et al. (2005) with the help of GIS and CA, has been able to extract information from high resolution remotely sensed imagery. Fuzzy sets have been used to represent the susceptibility of trees to mountain pine beetle because of the inherent uncertainty in dealing with geospatial data. Application of CA using GIS and fuzzy set theory has been made by Liu & Phinn (2003) to understand logistic trends of urban development process. When applied to an artificial city it produced realistic results proving the model to be theoretically valid and feasible. Calibration of this model to simulate actual urban development is a future scope for improving this model.

Integration of fuzzy logic, CA and GIS is a daunting task. In almost all real world modelling applications parameters can be better constrained by a set of fuzzy rules instead of sharp and hard constraints. There is often a sense of vagueness in real-world scenarios which can only be addressed by soft rules – usually by defining a percentage of membership to a particular class. A simple example illustrates the idea. Suppose, if the value of a variable exceeds 5 we assign it to class A, and if it is less than or equal to 5 we assign it to class B. This classification rule can be written formally as:

Integration of fuzzy logic, CA and GIS is a daunting task. In almost all real world modelling applications parameters can be better constrained by a set of fuzzy rules instead of sharp and hard constraints. There is often a sense of vagueness in real-world scenarios which can only be addressed by soft rules – usually by defining a percentage of membership to a particular class. A simple example illustrates the idea. Suppose, if the value of a variable exceeds 5 we assign it to class A, and if it is less than or equal to 5 we assign it to class B. This classification rule can be written formally as:

$$f(x) = \begin{cases} A, & x > 5 \\ B, & x \leq 5 \end{cases}$$

This is an example of a hard classifier. Thus, if x = 5.001, then it will be assigned to class B although it exceeds the threshold by only a small amount. A fuzzy classifier would on the other hand, be formulated where x = 5.001 would be classified as belonging to both class B and class A – say belonging 55% to class B and 45% to class A. Qualitative indicators to land use/

cover growth can be well represented by fuzzy sets. Instead of classifying a factor as positive or negative (binary classification) to the growth of, say, agricultural lands; the factors could be assigned fuzzy memberships to these classes and given weights proportionately to their range of impact. Although this is bound to produce some inaccuracies in the results, since the appropriate percentage of membership cannot be evaluated directly – the magnitude of the error will be much less than that for a hard classifier. In the same way, uncertainties with fuzzy logic can be extended to other models such as Cellular Automata. The neighbourhood of cellular automata may be modelled as a fuzzy set. Instead of taking into account the exact cells (as in Moore & von Neumann neighbourhood), one can, and for example, use an exponentially decaying function to evaluate the influence of the neighbouring cells on the cell in question, hence modelling it as a fuzzy logic.This is an example of a hard classifier. Thus, if x = 5.001, then it will be assigned to class B although it exceeds the threshold by only a small amount. A fuzzy classifier would on the other hand, be formulated where x = 5.001 would be classified as belonging to both class B and class A – say belonging 55% to class B and 45% to class A. Qualitative indicators to land use/ cover growth can be well represented by fuzzy sets. Instead of classifying a factor as positive or negative (binary classification) to the growth of, say, agricultural lands; the factors could be assigned fuzzy memberships to these classes and given weights proportionately to their range of impact. Although this is bound to produce some inaccuracies in the results, since the appropriate percentage of membership cannot be evaluated directly – the magnitude of the error will be much less than that for a hard classifier. In the same way, uncertainties with fuzzy logic can be extended to other models such as Cellular Automata. The neighbourhood of cellular automata may be modelled as a fuzzy set. Instead of taking into account the exact cells (as in Moore & von Neumann neighbourhood), one can, and for example, use an exponentially decaying function to evaluate the influence of the neighbouring cells on the cell in question, hence modelling it as a fuzzy logic.

Natural dynamics like forest fires and soil erosion has also been modeled by using CA. A CA model for prediction of the spread of forest fires in homogeneous and heterogeneous forests incorporating weather and land conditions has been studied by Karafyllidis & Thanailakis (1997). They developed an algorithm based on this model which gave results in agreement with fire spreading in real forests, when tested on hypothetical forests. A CA model for soil erosion by water was developed by Ambrosio et al. (2000). It considered a larger number of states including altitude, water depth, total head, vegetation density, infiltration, erosion, sediment transport, deposition etc., which were absent in previously developed models of this nature. Moreover, these hybrid methods have been found to perform better than existing methods. A self-modifying CA simulation model has been developed by Hoppen et al. (1995) wherein the control parameters of the model are allowed to self-modify so that the CA adapts itself to the circumstances. Katiyar & Arun (2014) has identified the need of methodologies to increase feature recovery from under sampled images. An intelligent adaptive re-sampling methodology was studied by them. This technique adapts by itself based on the texture and pixel validation in the image. It was found that the proposed hybrid method based on CNN was found to perform better than existing methods because of its ability to adapt itself with respect to the features of the image.

A patch based CA model was a new development in this domain which decreased the complexity of handling the large amount of spatial data used during simulation. A fine resolution CA model was developed by Wang (2012) to model complexity which increases dramatically due to increased number of classes or categories of the way the land is being used. A theoretical approach was adopted to identify the driving factor for calibrating the model. His paper proposed an innovative patch-based CA model to simulate land use changes. The model was tested under various development scenarios establishing that increasing the land use efficiency of an area is a good way to reduce the effects of rapid population growth. Landscape pattern indexes were used by Yang et al. (2014) to propose a land use change simulation model by integrating CA and Markov chain.

Accuracies and uncertainties in the modeling and simulation of land growth using CA models were also addressed by a number of authors. Wang et al. (2012) have focused their study mainly on the accuracy and uncertainty metrics of previous studies made with the help of CA-Markov model. The accuracy was measured by the Kappa index for different cell sizes and neighborhoods. It was established that smaller cell sizes give more accurate results although the run time of such algorithms is high. Their study allowed determining which cell size and neighborhood will give the best results for simulation. Errors and uncertainties in urban CA have also been discussed by Gar-On Yeh et al. (2002). They have identified that errors in data can propagate through the CA modeling process which impacts the outcome of the urban simulations. While trying to overcome these, it was also noticed by the authors that the characteristics of these errors are unique and are different from the ones present in traditional GIS models. Calibration of urbanization models using CA has not been given enough attention according to de Almeida et al. (2003). He presents a structure for modeling urban change by estimating land use transitions using elementary probabilistic methods inspired by Bayes' Theorem and other related concepts like the "weights of evidence" approach.

Different predictions were made in the implementation phase and the data was statistically validated by a multiple resolution fitting procedure. Pan et al. (2010) has identified the need of a study of scale in the context of land use research and CA models. Impacts of variation in scale in a CA land use model have been researched. Different scales to represent different spatial resolution of the images, cell sizes and different neighborhood configurations yielded varying results of land use transitions. Logistic regression has also been a widely applied technique in calculating the probabilities. Proximity based transitional functions and Bayesian probability methods along with CA and Markov chains proved to be a good combination in analyzing real world land use change. Integration of socio-economic data in some of these models has opened new dimensions in prediction of land use dynamics. Soares-Filho et al. (2002) has developed DINIMICA which is a spatially explicit simulation model of landscape dynamics. The said model is based on CA and presents multi-scale proximity based transitional functions, incorporation of spatial feedback mechanism to a stochastic multi-step simulation engine and a logistic regression to calculate the spatial dynamic transition probabilities. It was found by Kocabas & Dragicevic (2007) that CA models do not adequately take into account the interrelationship between variables, although there are interactions in the real world of land use change. A CA model integrated with GIS has been developed with weightage given to these shortfalls by considering Bayesian Network (BN) and Influence Diagram sub-models. The results of the study indicate that the model is quite suitable for detecting spatio-temporal drivers and generate scenarios to explore complex planning problems. DINIMICA and Bayesian probability methods, as discussed above, was also used by Almeida et al. (2005) to build methodological guidelines for modeling land use change in an urban environment. Logistic regression was also used by Arsanjani et al. (2013) along with Markov Chain and CA to present a hybrid model which showed improvement the performance of classical logistic regression model.

A paper by Sang et al. (2010) has proposed a method for simulation of spatial patterns consisting of two parts: quantitative forecast using a Markov model and spatial pattern change simulation using the CA model. The quantity and spatial pattern changing characteristics have been integrated and applied by the authors. Similarly the combined forces of Markov analysis and CA have been used by Guan et al. (2011) to model and analyze spatiotemporal changes. Socio-economic data were also given a weightage in the process to obtain the transformation matrices which in turn were used to predict the future land use changes. The concept of logistic regression has also been used by Munshi et al. (2014) to calculate a probability surface of a development transition while CA was used to model the spatial interaction used to simulate urban growth.

With population increasing rapidly, especially in the urban areas of developing countries, the extent of urban areas was also on the rise. Cellular automata were used to find a solution to this urban sprawl by fine tuning transition rules especially for an urban environment. Urban sprawl has also been studied in this context. Spatio-temporal data can be used to model urban sprawl's pattern and extent making it possible to predict the nature of its future. Sudhira et al. (2003) has been able to measure the extent of it over a period of three decades and attempted to describe metrics required for quantifying the extent of the sprawl. Li et al. (2008) has provided a new method for accessing, evaluating and modifying urban signatures for simulating compact development of urban areas using CA. Subdividing large urban areas can facilitate the use of separate transition rules to simulate better results. Apart from that, urban development signatures from one sub region can be applied to another one for producing better urban forms. Urban sprawl has also been studied by Deep & Saklani (2014) using a CA-Markov model. The validation of the prediction made by the developed model gave a Kappa coefficient of 0.91 which indicated the suitability of the model to predict the future. Studies on urban sprawl using CA are still found to be a popular topic of research in this domain. Principal Component Analysis (PCA) and Multicriteria evaluation (MCE) have been used as a technique in the methodology for various purposes by different authors. Integration of CA, PCA and GIS techniques has been discussed by Li & Yeh (2002). It pointed out the disadvantages of using a MCE and provided an easier way to handle a large amount of spatial variables for the implementation of the CA model. A paper by Sietchiping (2004) shows why Informal Settlement planning approaches formulated in developed countries fail to work in developing countries. It has used a CA model attached to a GIS to simulate the spread of informal settlements. A new CA model to predict future urban growth has been developed by Maithani (2011). GIS and Markov chain process were used for calculating the amount of land required for future urban growth. He also used MCE to reveal relationships between future urban growth potential. A CA model was used to spatially allocate the calculated amount of land based on urban suitability information provided by MCE and Markov chain process. The model was evaluated using Kappa Coefficients.

Use of CA-Markov chain in various domains:

Application of cellular automata to model real world scenario has started at least 15 years ago (Fig.2). Although methodologies furnish a solid base to provide the much-needed theoretical support, the actual implementation of the models is a huge challenge to the scientists. Considering the nature of spatiotemporal dynamics in the real world, it requires a huge number of variables and factors to model the environment to a realistic threshold. Grassland protection using CA was implemented by Li & Yeh (2001) and He et al. (2005) during the 2000s. Rapid urbanization and consequent conversion of grasslands to urban regions gave researchers an opportunity to help the situation. Li & Yeh (2001) has also overcome the shortfalls of traditional zoning methods and a constrained CA model has been implemented. Gray cell concept was also used in testing the model and improving its accuracy. Remote sensing and CA has been used for zoning grassland protection area by He et al. (2005). It was observed by them that RS, on its own, cannot locate suitable areas for zoning. To overcome this shortfall, an integrated RS and CA model has been developed and implemented as a case study. CA and GIS models were integrated to calibrate cellular automata to the real world. Help of social and economic data were taken in order to better understand the reasons and influences of why and how cities are grasping their neighborhoods so fast. All these were supplemented by the better technology at hand with the launch of modern satellites with exceptional sensors on board that provided accurate and detailed remotely sensed imagery with high spatial resolutions. Loose coupling of a CA model and GIS was done to predict long-term growth in an urban environment by Clarke et al. (1998). Considering two fast-growing urban areas in the US, the said model was applied to both predict and calibrate data. The role of GIS in the application of the model was discussed and the results produced were found to be consistent with other models and actual growth observations. RS imagery and socio-economic data has been integrated and implemented along with GIS to better understand the spatiotemporal dynamics of the growth of a city by Mundia & Aniya (2005).

Relations between land cover and land use dynamics were found by Brown et al. (2000). Socio-economic data again came to the help in establishing this link. On a side note, forest cover change was also simulated using a CA-Markov model by Adhikari & Southworth (2012). In a paper by Brown et al. (2000) land cover change was modeled to be a function of land use change. They tried to point out that land use and land cover change needs to be represented as separate processes when modeling the link between socio-economic and forest cover changes. Forest cover change simulation was also performed by Adhikari et al. (2012) using a CA-Markov model and a RS technique. The model was implemented on Bannerghatta National Park and it showed the usefulness of this model to evaluate conservational efforts. Since the beginning of the new millennium, along with considerable development in the invention of new methodologies, came the application of them to the real world scenario. Stochastic modeling and application of statistical methods like Markov modeling and Monte-Carlo methods were applied. Ward et al. (1999) used remotely sensed images for spatiotemporal studies of urban land cover characteristics. These works show the potential of moderate spatial resolution images of the current and next generation RS images to help in urban studies. Weng (2001) has investigated the land use change dynamics using RS images, GIS and stochastic modeling. The study has shown the integration of RS and GIS is an effective approach for measuring land use change.

Markov modeling was also found to be beneficial for describing the change process. An assessment of urban development plan was made by Chen et al. (2002). An adaptive Monte-Carlo method was used to calibrate factor weights in the CA transition rules. Future urban scenarios have been simulated by Barredo et al. (2002) using CA. They have applied the model to the city of Dublin and it was tested by fractal dimensions and comparison matrix methods. The results were found to be realistic and quite accurate confirming the suitability of the urban CA model. Calibration of these stochastic CA models was done by a large number of researchers, with Wu (2002) being one of them. He had introduced MCE and artificial neural networks to systematize the existing calibration process which was heuristic in nature. Calibration of stochastic CA was used in the application to rural-urban land conversions by Wu (2002). It was observed by Wu (2002) that until recently the calibration phase of CA was largely heuristic. It was the incorporation of MCE and Artificial Neural Networks that brought a systematic approach to the procedure. His study, therefore, concentrated on the application of the calibrated CA process to simulate conversion of rural lands to urban ones. His study also suggested the need for examining the result of CA through various validation methods. Future LULCC was predicted using a CA-Markov model by Kamusoko et al. (2008). They had adopted a MCE procedure to generate transition potential maps from biophysical and socio-economic data. A study on detection and prediction of land use change using RS and GIS has been done by Huang et al. (2008). A Markov model was applied for predicting the future land cover. The study yielded an overall accuracy of 80%. Prediction mechanisms of future land use and land cover changes were thus developed. People were interested in knowing where they will stand in a decade, say, if growth continued the way it was. Connection of urban growth relative to the road networks in a city and how the former depends on the later were done by a handful of researchers. A similar study to model the urban growth was made by Moghadam & Helbich (2013) using CA-Markov chain analysis for spatiotemporal urbanization in a megacity. An integrated CA-Markov model was implemented along with MCE to generate the transition probability maps. A future prediction was made for the growth rate and the expansion along the main traffic infrastructure is expected to occur. This gives hints of the potential for a CA-Markov model to find a relationship between two urban features like growth and road networks. Integrated system dynamics and CA were applied to assess urban growth by Han et al. (2009). The procedures included socioeconomic driving forces analysis and urban spatial pattern evaluation. The spatiotemporal variability of urban expansion has been studied and analyzed using GIS technologies. Markov, transfer matrix, and trajectory analysis has been performed to find the relationship between GDP, population and urban land areas are built up using regression analysis.

Research on RS and GIS applied to coastal land use pattern study using CA was made by Henriques & Tenedório (2009) and they had derived the advantages and disadvantages of CA to model coastal floodable areas that are environmentally fragile. Application of integrated system dynamics and CA was performed by Han et al. (2009) for the purpose of urban growth assessment. Socio-economic data driving force analysis was performed and it was found that the model was competent in monitoring and projecting the urban growth dynamics. A relation between road network planning and direction of development in newly urbanized territories were also found. CA-Markov, Stochastic Markov and Multilayer Perceptron Model (MLP) – three different methodologies have been used after a Fisher supervised classification on base maps by Ahmed & Ahmed (2012) to analyze the future urban growth of Dhaka. Markov modeling, by this decade, had become popular enough to see widespread application to the geospatial domain, especially in conjunction with Cellular Automata. A CA-Markov model has been implemented by Behera et al. (2012) to study LULC dynamics and predict its nature in the future in terms of magnitude and direction. Analysis of socio-economic data has also been performed in the simulation process. Land use and land cover changes were widely being studied with the help of a variety of CA-Markov models. Their ability to predict the future scenario made these hybrid models quite lucrative to be used by the researchers. A probabilistic CA-Markov model has been used to evaluate the dynamics of simulated LULC by Xu et al. (2013). A CA-Markov model was used alongside GIS in monitoring and predicting land use change in an urban environment by Al-sharif & Pradhan (2014). The future land use prediction was made after calibrating the model using transition rules and transition area matrices derived from CA-Markov analysis. Spatiotemporal distribution of urban land use was studied by Nouri et al. (2014) using a CA-Markov model. Using transition matrices, future land use scenarios were simulated and growth patterns were predicted. Cellular Automata was applied by Mubea et al. (2014) for simulation and assessment of urban growth scenario using a Cellular Automata Urban Growth Model. Multi-temporal satellite imageries were used along with data like road data, slope data and exclusion layer to simulate urban land use scenario for the future using a Monte Carlo technique. The study showed that Urban Growth Model (UGM) can be an alternate solution for planning purposes for sustainable development in an area. The UGM demonstrated its power by providing quantitative, visual, spatial and temporal information as output to policy and decision makers to help them in making an informed decision. Land cover change using a CA-Markov model was studied by Yagoub et al. (2014) using RS imagery. Markov-CA model was also discussed in context of detection and prediction of LULCC by Halmy et al. (2015). The results of the study were found to be comparable to the actual LULC changes. Projection and modeling of LULCC taking into account the landscape trajectories was also made by Houet & Hubert-Moy (2006) using CA. The combined effects of land use and climatic change were studied in a Markov-CA environment by Louca et al. (2015). A bioclimatic model was established by them and future land use scenarios were modeled using the transition probabilities derived from CA-Markov analysis.

LULCC using a CA-Markov model was also studied by Ye & Bai (2008) along with RS and GIS methods. A spatial land use pattern reconstruction model using CA-Markov was implemented by Yang et al. (2015) to simulate historical land use. Validation metrics were used for the simulation of LULCC to calibrate the change predicted by CA Markov analysis by Memarian et al. (2012). CA-Markov was found to be unsuitable due to poor performance during the simulation due to uncertainties in data source, the model and the processes of LULC change in the study area. CA-Markov modeling has been used by Gong et al. (2014) to simulate land use spatial pattern and project the results to the future by following the trajectories. A CA-Markov model has also been used to study the dynamics of landscape pattern in an inland river delta. This study by Mambetov et al. (2014) also investigated the effectiveness of using a CA-Markov model for analyzing wetland landscape pattern dynamics. It was found that the model is effective and valuable for land management strategies. A CA approach was adopted by Leguizamón (2006), and applied to describe the changes in vegetation. It was found that the problems of RS can be easily overcome by using CA techniques.

Applications of Cellular automata models were done in studying a variety of subjects. They were found to be applied for the study of biologically invasive plants' growth and demonstrated realistic and accurate results in a wetland environment. Salinization and desalinization studies were also made a few years ago to test the viability of using a CA-Markov model for simulating such unobvious phenomenon. A similar study was conducted by Huang et al. (2007) to model the population expansion of *Spartina alterniflora* – a biologically invasive plant using a CA model. Remote Sensing technology along with GIS had been used to demonstrate the potential of the approach to extract insights into the population and community ecology of invasive plant species. This in turn could prove to be very important in respect to wetland biodiversity conservation and resource management. A unique research has been conducted by Zhou et al. (2012) to model land salinization and desalinization processes. A CA-Markov model was used for regional assessments and simulations proving it to be a valuable and alternative tool for the work. Their study suggested that this model when fed with biophysical and human induced data performed better than those without this data. Different soil management scenarios for salinity management could be tested using this model. A CA-Markov model was used by Barona Cabrera & Mena (2014) to study the future spread of an invasive plant namely Psidium guajava. A LULCC model, namely GEOMOD was used in conjunction to the CA model to calculate the prediction map of the spread of the plant and also to validate the map by comparing it to the Markov chains prediction map. People being curious to know what would happen if something else were the case, influenced the use of fuzzy logic to study the rural land encroachment issue as early as 1998 using CA and GIS controlled by a set of fuzzy logical rules. The phenomenon of rural land being encroached upon by urban ones has been studied with the help of GIS and fuzzy logic controlled CA by Wu, 1998. A computer-based approach has been adopted for the simulation process and the power of fuzzy logic was used to simulate the land conversion scenario. On the other hand, CA was used for extracting a global pattern from simpler local rules. A novel Artificial Immune System based CA model was implemented by Liu et al., 2009 to simulate land use dynamics where planning policies have been implemented. Various land use policies were studied under the influence of different scenarios so that the planners could answer “what-if” questions and thus evaluate the options at hand. Their study demonstrated the model to be useful in exploring planning scenarios in an urban environment.

Most recent works:

Halmy et al. (2015) had studied the LULCC in the northwestern desert region of Egypt using an integrated Markov-CA approach and had attempted to predict the future land use scenario. Landsat TM5 data along with data from other sources were used for the work using a "random forest" approach which yielded an overall accuracy of about 90%. Land use of the region was projected till the year 2023, and the authors expect this kind of a study will, in the future, help study LULCC phenomenon in dry and arid regions of the world. Gong et al. (2014) had used a combined CA-Markov approach to observe the land use change due to rapid urbanization and population growth in the north-eastern region of China - a significant grain-producing part of the country. Combined with RS and GIS, the authors studied the LULCC in the area and predicted the same for the future. Olmedo et al. (2015) had invented a procedure to compare the outputs of models simulating change of categories from one to another over time in general. In his paper, he had used two land change models: "Land Change Modeler" and "CA-Markov to demonstrate how the choice of the model used to simulate LULCC effectively influence the quantity of land allocated to each category. They had also created a method to actually compare the results of any two model runs with respect to a reference map of transitions during the period of time over which it is being validated. The scope of CA and Markov model in simulating urban land use change had been studied by Huang et al. (2015). Due to the factor of randomness in the real world, it is difficult to predict land use change using traditional methods. To cater for this factor, a Markov - CA model had been used by the authors in order to simulate the land use change in the region of Wuhan, China. The transition rules of the model were constrained to global and local factors along and a random variable was included to simulate the land use change as accurately as possible. To understand the interactions between humans and the environment from a long-term perspective, it is necessary to reconstruct the historical LULCC. LULCC being recognized as a key factor in driving a global environmental change and it is also considered as a key for understanding and balancing energy use. In this regard, the paper by Yang et al. (2015) had studied and attempted to reconstruct the historical land use land cover change (LULCC) of the 1930s in Zhenlai County, China using a CA-Markov based model. Multi temporal remotely sensed images were used to extract urban evolution rules using self-adaptive Cellular Automata. Large systems being difficult to model and parameterize using traditional CA methods, the study by He et al. (2015) used a self-adaptive CA along with artificial immune system to discover dynamic transition rules. The model's parameters being allowed to self-modify themselves, the rules can adapt to complex changing environments. Quantitative index Figure of Merit along with pattern similarity techniques were also used for comparing Logistics CA and AIS-based CA models and it was found that AIS-based CA models outperformed Logistics-based CA models by being more accurate and precise. Urban expansion patterns and the threat it poses to the ecology has been assessed by Liu et al. (2015). A hybrid model has been devised using auto-logistic regression, Markov chain and cellular automata by them to improve upon standard logistics regression model. An eco-risk assessment index was established to effectively and dynamically evaluating the environment and the eco-security. Al-Sharif & Pradhan (2015) presented a novel approach for prediction of spatial patterns of urban expansion by incorporating a hybrid Chi-Squared automatic Integration Detection - Decision tree (CHAID-DT), Markov chains and CA models. The proposed model was implemented on the city of Tripoli, Libya. It was observed by Feng et al. (2015) that linear methods are insufficient for simulating complex boundaries between urban and non-urban areas. Their paper discusses a machine learning CA model using non-linear transition rules based on least-squares Support Vector Machines (SVM) for simulating urban growth. The developed CA model was implemented in Qingpu-Songjiang area in Shanghai, China. Later the Machine Learning CA model was compared with conventional CA methods using logarithmic regression, and it was found that the Machine Learning CA model provided more accurate and reliable results. In a paper by Bozkaya et al. (2015), the authors had tried to develop a model that could quantitatively present the changes in LULC and its impact on Igneada landscapes in Turkey in the future. They had used Markov chain based Stochastic Markov model as well as CA based Markov models. It was found by the authors that CA based Markov model yielded more accurate results in comparison to Stochastic Markov model. Logistic regression and Markov chains based on CA were used to assess and simulate the urban growth potential of Istanbul in Turkey by Akin et al. (2015). Fathizad et al. (2015) studied multi temporal satellite images for detecting LULCC and forecast the same for the future in a semi-arid western region of Iran. MLP was applied for a supervised classification of land use. Classifying the region into five different categories, the changes for the year 2021 were predicted using a Markov chain model. CA based Markov chain model was used by Singh et al. (2015) to study the spatial and temporal LULC changes. Using images of the year 1990 and 2000 as inputs, the results were validated by another image from 2010 and a prediction for the year 2020 was made by using the CA-based Markov model. Two urbanization indexes namely Land Consumption Ratio (LCR) and Land Absorption Coefficient (LAC) were also calculated for quantifying urbanization. In a paper by Nadoushan et al. (2015), LULCC in Arak was categorized by both visual interpretation of aerial photos and ANN based classification - both yielding an overall accuracy of 95%. CA based Markov model was also used by the authors to predict and simulate the future and derive a LULC map for the year 2025.

Limitations:

Kamusoko et al., (2008) pointed out that a limitation of CA-Markov analysis was the non-accountability of human influences and government policies that affect the behaviour of the farmers and occupants of the land while modelling a situation. Unavailability of high resolution imagery also limits the power of CA-Markov analysis. Zhou et al. (2012), for example, had studied the salinization and desalinization of land through a CA-Markov model. However, due to the unavailability of high resolution imagery of socio-economic driving factors affecting the salinity, these causes were not accounted for in the study by the authors. Thus, only the natural causes for change in salinity was done hence some inaccuracies had crept in to their study. Yagoub et al. (2014) said that one of the main limitations of a CA-Markov model is that the factors that drove the change in land use in the past are assumed to remain the same during the future. Since this is not so in the real world, it leads to errors during simulation. For example, their studies had chosen images for only 3 years for studying the trend while the results were validated using data from another 3 years which were of different seasons. Hence, the effect of seasonal change in land use was present and this lead to some inaccuracies in the study.

While discussing about the integration of CA with GIS, it was noted by Wagner (1995) that the primary discrepancy between the two lies in the cell states of CA and the attribute values of GIS. The discrete values of the cell states in CA are not sufficient to represent the continuous or discrete nature of an attribute in GIS. It was also noted that the development of new GIS operators and CA transition rules are very important and obvious for the development of this process of integration. Yang et al. (2014) observed that the main limitation of the study was the subdivision methodology to divide a piece of land into smaller regions. The transition of the same land use classes into different regions during this subdivision process must be avoided and is a scope for future research. One of the limitations observed by Xin et al. (2012) was that the factor of human decision making was absolutely absent in their ACO-CA model. Hegde et al. (2007) in their study of integration of CA and GIS systems objectively identified some possible errors. They were broadly the discrete nature of space and time in CA, the variety of neighbourhood definitions – the variety in their shape and size, the model structures and transition rules for evolution of the CA, and the values of different parameters which are taken as an input. A neural network based CA model has been proposed by the authors with 3 layer architecture – one for the input variables, one for the output map and another hidden layer controlling the non-linearity of the network.

Logistic regression, cellular automata and Markov modelling were all tried to be integrated by Arsanjani et al. (2011). In the attempt many limitations to this model were observed and were tried to be rectified to a certain extent. Some limitations were, for example, not giving weightage to human decision variables in the simulation – the non-factoring of personal preferences and government policies were and still are limitations to the integration of

CA and Markov models in analysing and simulating urban growth. Agent based modelling (ABM) has been provided as a possible solution to these problems by the authors. In the study by Pan et al. (2007) it was noted that the a limitation in their study on the effect of scale on CA based land use change modelling was that smaller cell and neighbourhood sizes led to inaccuracies in the transition rules and in the simulation of the land use change. A multi-ring shaped neighbourhood in the CA was recommended to be used in the future by the authors with varying weights decreasing with the distance from the centre. This however, (as pointed out by them) would increase both the uncertainty and complexity of the model. The usage of fuzzy logic in Geo information modelling was pointed out by Bone et al. (2005). According to them, excluding fuzzy logic and incorporating discrete states in an insect infestation model (such as theirs), would give information about insect-induced tree mortality rate. On the other hand including fuzzy sets would throw some light upon the relationship between insects and the trees. Yeh et al. (2001) pointed out that their CA model developed to study urban development could not incorporate social and non-geospatial factors because of the difficulty in their integration with CA. If incorporated in the future, it would be a welcome improvement to their proposed model. Li et al. (2008) remarked that using Genetic Algorithms to find the most suitable gene for each sub-region and using different transition rules for different regions instead of one unified transition rule for all the regions would enable to simulate an urban environment more accurately. He et al. (2008) noted that urban expansion dynamics (UED) model will never be able to simulate the real world because of its sheer complexity. Because of the simplified urban land use projections and Monte-Carlo based calibration process, the model is bound to retain some uncertainty. It was advised to treat the outputs not as an accurate simulation and prediction of the future and would be more helpful to treat them as scenario based patterns of urban expansion. This model, according to the authors, would also be helpful for studying the impacts on environment and ecology because of the rapid urban expansion process. Some more limitations in this type of study were identified by Deep et al. (2014). In their study on urban sprawl using CA, it was noticed that inclusion of socio-economic factors would have improved the results of their study. Sang et al. (2010) also cited exclusion of socio-economic factors in their study on land use patterns using CA as a major limitation of their study.

Further Scope:

Espinola et al. (2010) observed that there is immense scope in the field of ACA. Developing and implementing new versions of ACA algorithms can be thought upon to fine tune the classification process. Parallel processing technology may also be applied for processing different areas of an image simultaneously in order to reduce computational cost. An ERDAS Imagine plug-in may be developed to make detailed customization of the classification operation using CA. Espinola et al. (2015) opined that inclusion of different state configurations and transition rules in the CA may be made in the future. Inclusion of fuzzy logic was also considered by the authors. The possibility of textural classification using ACA was also proposed by the authors. As a future scope of work in integrating CA and fuzzy sets, some authors have suggested exploring the effects of changing fuzzy set membership functions on the results produced by the CA model. Removing biases in simulation due to large CA cells and taking into account different scales of observations - thereby adopting a multiscale approach - are some future scopes of work, as suggested by Pinto et al. (2010). Harikrishnan & Poongodi (2015), has planned of developing a new version of CA based on neural networks in the near future. Wang, (2012) emphasized that while concluding their study on patch based CA model, that instead of relying on predefined input parameters during the process of simulation – which may not be available at some point in the simulation – an automated process may be developed relying only on transition probability maps. The model did not take into account any shape parameters to mimic actual growth development of a piece of land. Future work with a shape index model as an input parameter may be developed. In their study, the extent of the city limits was not considered. These data along with future transport networks and locations of environmentally fragile and important areas may be incorporated for a more accurate study. Wang et al. (2012) noted that researchers had focused their attention to the analysis of different parameters in a CA model, but had overlooked the actual impact caused by these parameter. Developments of new validation metrics could also provide a better accuracy assessment of CA based methods in the future.

De Almeida et al. (2003) threw light on future plans of developing a CA-based 2D and 3D land use simulation module which could be integrated into the SPRING GIS software. The module has been conceived as an integrated, flexible, multi-scale and multipurpose device. Work on the loose coupling of CA and GIS has been suggested by the authors for future development of CA in the geospatial domain. de Almeida et al. (2003) observed that since their “weights of evidence” is a flexible statistical tool and does not impose any kind of theoretical conformation rules – their proposed model can be used anywhere in the world where the pre-requisite information are available. 3D visualizations of land use change simulation models have been studied extensively in various previous literatures. Lloret et al. (2008) explored the avenues of developing visualization tools to project the land use / land cover change in the future by the process of simulation of the land use dynamics. GIS and 3D visualization have also been incorporated by Bell et al. (2000). 3D urban models with the help of GIS have been developed by Koninger & Bartel (1997). 3D urban models have also been proposed by Shiode (2001). These visual implementations of land use models can be tied up with Cellular automata to produce a 3D CA-Markov model with 3D neighbourhoods and 3D transition space. This integration could result in better modelling of real-world scenarios. The third dimension can be the elevation or some other parameter suitable for the purpose of the particular study. Implementation and development of these 3D CA and GIS techniques are being currently explored by a number of researchers including de Almedia et al. (2002). If successful, it is expected to be a major breakthrough in CA-Markov applications in the geospatial domain.

Takeyama & Couclelis (1997) studied a generalization of CA within a Map Algebra framework. They had come to the conclusion that this could open up new avenues of Map Algebra and CA in a variety of fields like design, learning and design. Guan et al. (2011) points out that the CA-Markov model that they have developed can be further improved by using Markov modelling to extract transition rules of the CA. Karafydillis et al. (1996), presented a forest fire spreading model with a scope of developing future algorithms that simulate the spreading of fire in real forests instead of hypothetical forests as developed in their study. They have also said that utilizing the concept of parallel computing, their model can be extended for developing a decision support system in a real-time scenario. Li & Yeh (2004) pointed out that future studies on the technique of data mining transition rules of a CA could concentrate on studying the discrete time steps on the results of the simulations. Optimal intervals between simulation and observation are also a prospective future field of research in this domain, according to the authors. Sietchiping (2004), while studying informal settlement simulation pointed out that incorporating agent based modelling techniques within their developed framework would contribute towards a more accurate simulation. Investigating uncertainties and complexities also remain a relatively untouched area in this domain of research. From an operational point of view, a more user-friendly interactive module can be potentially developed from the proposed informal settlement growth model to help urban planners make more informed decisions.

Clarke & Gaydos (1998) after studying the San Francisco Bay Area with the help of a self-modifying CA model, planned to explore the same region with the model to produce three different animated growth predictions. In this way, the authors believe, one can predict the urban growth on a national scale using an Advanced Very High Resolution Radiometer (AVHRR) so that the future environmental consequences can be visualized and anticipated. In the study by Li & Yeh (2001) the authors had used artificial neural networks to simulate urban systems. During their study they noted that multiple land use scenario modelling by neural networks is yet to be done. Simulation of 'planned development' instead of the development that is actually happening is to be given more stress and optimizing the number of neurons and their layers should be researched upon since it is an inherent shortcoming of a ANN. Sante et al. (2010) have suggested that further developments in CA based growth model could include new validation metrics and integration with conventional geographical and urban theories to give this concept a theoretical foundation. They have also remarked that these models should, instead of attempting to predict the future accurately, try to give a parametric solution to a problem whereby different scenarios could be tested or studied by altering one or more of the parameter variables. Rabbani et al. (2012) used particle swarm optimization alongside CA and had noticed that optimization techniques are necessary to define the most suitable threshold on different input factors since trial and error in this case, is not an option because it gives different results for different values. It was also noticed that a CA model cannot accurately model change in a distant patches of land which are isolated from the main chunks as CA, by nature, involves the local neighbourhood as the input for defining its transition rules. It was noted that hand in hand with urbanization adequate weightage on de-urbanization should also be given in order to get more improved results from the simulation.

In Li & Yeh (2001) a constrained CA model was used for zoning lands with a hope for agricultural protection. However, the scope of application of the model to other domains like environmental planning and management were recognized by the authors., Similarly the approach adopted by Mundia & Aniya (2005) could be applied to study areas in developing countries where RS and GIS data are limited, inaccurate or blatantly unavailable. Huang et al. (2008) noted that further studies should be made on the impact and interactions of spatial variables with each other during the modelling and simulation of urban growth. Socio-economic factors must also be given appropriate weightage in the model according to the authors. Luo et al. (2014), observed some inconsistency of source data which affected the projection made by their implemented CA-Markov model. Their model could be further used by land managers and planners eager to build an early warning system for potential landscape feature changes. Weng (2011) has said that the image classification method that was used in his study was not spatially implicit – and therefore, the image classification accuracy was a big limitation in his study. Higher order effects were also difficult to implement in his model. A second order model, which would include m^2 states instead of only m states in the Markov model, would be difficult to integrate in a Markovian analysis of land use change. Non-stationery transitions were also something that would be difficult to model. The non-dependence of spatial transitions on simple constraint-transition models was also a limitation for an attempt to integrate the said fields in the domain of land use land cover change analysis. The lack of widespread appreciation of the power and ability of Markov modelling in land use change models was also said to be a hindrance to future research. Halmy et al. (2015) has cited the need for more studies to document the LULC changes through the concept of CA-Markov Analysis which shows promise. Integration of socio-economic variables to understand the cause and effects of LULCC were also recommended by the authors. Recently Louca et al. (2015) had attempted to combine bioclimatic modelling with CA-Markov analysis to study land use change and found that there were several limitations to their approach. Spatial and temporal resolution mismatch between the bioclimatic and species distribution data and the possibility of sampling bias on the species distribution data were the major ones as pointed out by the authors. They had also noticed that the inclusion of more parameters bring the necessity for assumptions which result in the uncertainty of the results. Since these assumptions had to be made to simplify the simulation and modelling, letting go of these assumptions and increasing the complexity will certainly bring generality of the results into the picture. Decoupling the concepts of land use and bioclimatic change and applying the CA-Markov model was also thought of by the authors but was not implemented in their study. This process may shed some light on the interactions between the two, though it is conceptually difficult to perform such detangling of phenomenon highly dependent on one another. Singh et al. (2015) noted that their CA-Markov based prediction model could be improved using socio-economic data and also integrating the effects of government policies which would influence urban growth. Henriques & Tenedório (2009) pointed out that it was necessary to test the strengths of a CA model to simulate land use change in areas where uncontrolled land occupancy is practised, for example, in some African cities. In the study by Adhikari et al. (2012), it was noted that the probabilistic nature of CA-Markov was not suited to in-depth study of the factors due to which forest cover changes. Therefore, the future use of socio-economic variables in a model was recommended for increasing accuracy. It emphasized the role of CA-Markov analysis in environmental policy planning at the national level. Barona et al. (2014) studied the spread of a biologically invasive plant species. The authors, as a scope of future research, cited the inclusion of various factors that affect plant spread into their developed models. These include socio economic factors and biotic factors - like the process of dissemination of the seeds by the birds and the mammals in the area etc. Use of advanced techniques for calculating sensitivity and uncertainty of the model were also planned by the authors. CA-Markov analysis imposes a spatial dependency due to its contiguity rule rendering the growth simulations for bare and grasslands as inaccurate, as it was found by Mermarian et al. (2012) that bare lands, in general, do not expand. This inaccuracy can be overcomed in future studies by considering the nature of the land cover under observation. Halmy et al. (2015) cited the need for more studies to document the LULC changes through the concept of CA-Markov Analysis which shows promise. Integration of socio-economic variables to understand the cause and effects of LULCC were also recommended by the authors. In Houet & Hubert-Moy (2006) it was noticed while attempting to find a relationship between landscape features and LULCC, that a CA-Markov model is a component of cyclic phenomenon. Thus, taking into account crop succession in a new CA model may prove to be a potential minefield of research in the future. In Ahmed & Ahmed (2012), they have studied the urban land cover growth development using multi-temporal satellite images. They have hoped that if the amount of error present in the base map is reduced then the future prediction of the land use change would be more accurate and help regional and local planners immensely in carrying out their ordeals. In Huang et al. (2007) the authors' study on the spread of an invasive plant revealed that such future studies on invasive species are the crux for discovering and understanding community ecology and is essential for the application of community theory in restoration ecology. In Han et al. (2009) it was noted as a conclusion that in their integrated system dynamics a CA model can be potentially used to quantitatively derive urban development policies by experimenting with the different policies in various spatial and socio-economic scenarios. It was also said that, in case detailed information about a region - such as GDP distribution, population density etc., are available to the geo-information system, their proposed model can be used to accurately estimate the urban growth of a region. In the study by Clarke & Gaydos (1998) it was said that the future scope of CA integration with GIS lies in the study of a broader classes of land use transitions. It was observed that repeated application of the same model over different areas considered at various scales, could also throw up interesting observations that would help planners and designers in anticipating and predicting urban land use scenarios, helping to thrust forward the urban future of the next generations towards the positive side. In the review by **Herold et al**. it was pointed out that along with land use data, socio-economic data should also be represented to study land use change. Spatial and temporal resolution mismatch should be reduced to increase the accuracy of the urban growth models. Moreover, road networks and topography must also be taken into account when modelling such studies in an urban environment. In a study by Wu (1997) which uses fuzzy logic to control CA in a GIS framework, the need for discovering realistic CA transition rules using general data discovery techniques like data mining was recognized. The CA neighbourhood's shape and size should be experimented with, and new ones need to be found using the said generalized knowledge discovery techniques. In the study by Moghadam & Helbich (2013), the authors had concentrated on the urbanization process in a megacity. Future studies should be directed towards evaluating different planning scenarios on land use dynamics.

Conclusion:

CA and Markov chain analysis, as seen from this study, have been widely used in conjunction with other techniques like logistic regression models. Accuracies and uncertainties in the results have also been given emphasis. However, there is much scope of development of new methodologies with the help of PCA and MCE. A comparative review of the results of PCA vs. MCE application in new methodology development is highly needed. Self-adapting CA models are also a great goldmine for future work. Use of genetic algorithms in classification methods has also been used sparingly and can be developed for further use. Application of CA/Markov rules in urban growth and LULCC has seen widespread application. Meanwhile use in the field of niche areas like Forest cover change simulation, coastal land management, wetlands landscape dynamics remain unexplored. Salinization and desalinization studies using CA / Markov model also need to be studied in the near future. Study of the spread of biologically invasive plants can also be easily modelled using CA. More or less, CA and Markov modelling have given promisingly accurate and reliable results in most of their applied fields of study in the geographic and spatial domain. It is certain that more studies will be done in the near future in developing new methodologies as well. It will be beneficial if the newly developed methods of use are applied to actual real world scenarios hand in hand, which will then create a virtuous cycle of development and application. The results of the test may be used as feedback for future developments of methods in order to rectify, correct and fine tune them according to the specific use or application.

Acknowledgements

This work has been done under the project 'Assessing Health, Livelihoods, Ecosystem Services and Poverty Alleviation in Populous Deltas [NERC Grant References: NE/J002755/1]' which was executed with funding support from the Ecosystem Services for Poverty Alleviation (ESPA) programme. The ESPA programme is funded by the Department for International Development (DFID), the Economic and Social Research Council (ESRC) and the Natural Environment Research Council (NERC). Authors are grateful to ESPA, DFID, ESRC and NERC

References

Adhikari, S., & Southworth, J. (2012). Simulating forest cover changes of Bannerghatta National Park based on a CA-Markov model: a remote sensing approach. Remote Sensing, 4(10), 3215-3243.

Ahmed, B., & Ahmed, R. (2012). Modeling Urban Land Cover Growth Dynamics Using Multi-Temporal Satellite Images: A Case Study of Dhaka, Bangladesh. ISPRS International Journal of Geo-Information, 1(1), 3-31.

Akin, A., Sunar, F., & Berberoğlu, S. (2015). Urban change analysis and future growth of Istanbul. Environmental monitoring and assessment, 187(8), 1-15.

Alkheder, S., Wang, J., & Shan, J. (2006, May). Change detection-Cellular automata method for urban growth modeling. In Proceedings of International Society of Photogrammetry and Remote Sensing Mid-term Symposium (Vol. 7, p. 5).

Almeida, C. M. D., Monteiro, A. M. V., Câmara, G., Soares-Filho, B. S., Cerqueira, G. C., Pennachin, C. L., & Batty, M. (2005). GIS and remote sensing as tools for the simulation of urban land-use change. International Journal of Remote Sensing, 26(4), 759-774.

Al-sharif, A. A., & Pradhan, B. (2014). Monitoring and predicting land use change in Tripoli Metropolitan City using an integrated Markov chain and cellular automata models in GIS. Arabian Journal of Geosciences, 7(10), 4291-4301.

Al-sharif, A. A., & Pradhan, B. (2015). A novel approach for predicting the spatial patterns of urban expansion by combining the chi-squared automatic integration detection decision tree, Markov chain and cellular automata models in GIS. Geocarto International, (ahead-of-print), 1-24.

Arsanjani, J. J., Helbich, M., Kainz, W., & Boloorani, A. D. (2013). Integration of logistic regression, Markov chain and cellular automata models to simulate urban expansion. International Journal of Applied Earth Observation and Geoinformation, 21, 265-275.

Barredo, J. I., Kasanko, M., McCormick, N., & Lavalle, C. (2003). Modelling dynamic spatial processes: simulation of urban future scenarios through cellular automata. Landscape and urban planning, 64(3), 145-160.

Behera, M. D., Borate, S. N., Panda, S. N., Behera, P. R., & Roy, P. S. (2012). Modelling and analyzing the watershed dynamics using Cellular Automata (CA)–Markov model–A geo-information based approach. Journal of earth system science, 121(4), 1011-1024.

Bell, M., Dean, C., & Blake, M. (2000). Forecasting the pattern of urban growth with PUP: a web-based model interfaced with GIS and 3D animation.Computers, Environment and Urban Systems, 24(6), 559-581.

Bone, C., Dragicevic, S., & Roberts, A. (2006). A fuzzy-constrained cellular automata model of forest insect infestations. Ecological Modelling, 192(1), 107-125.

Bozkaya, A. G., Balcik, F. B., Goksel, C., & Esbah, H. (2015). Forecasting land-cover growth using remotely sensed data: a case study of the Igneada protection area in Turkey. *Environmental monitoring and assessment*, *187*(3), 1-18.

Brown, D. G., Pijanowski, B. C., & Duh, J. D. (2000). Modeling the relationships between land use and land cover on private lands in the Upper Midwest, USA. Journal of Environmental Management, 59(4), 247-263.

Cabrera Barona, P. & Mena, C. (2014) Using cellular automata-marcov chains-GEOMOD model for the quantification of the future spread of an invasive plant: a case study of *Psidium guajava* in Isabela Island, Galapagos. International Journal of Geoinformatics, 10 (3), 23-30.

Chen, J., Gong, P., He, C., Luo, W., Tamura, M., & Shi, P. (2002). Assessment of the urban development plan of Beijing by using a CA-based urban growth model. Photogrammetric Engineering and Remote Sensing, 68(10), 1063-1072.

Clarke, K. C., & Gaydos, L. J. (1998). Loose-coupling a cellular automaton model and GIS: long-term urban growth prediction for San Francisco and Washington/Baltimore. International journal of geographical information science, 12(7), 699-714.

Clarke, K., Hoppen, S., & Gaydos, L. (1997). A self-modifying cellular automaton model of historical. Environ Plan B, 24, 247-261.

Couclelis, H. (1997). From cellular automata to urban models: new principles for model development and implementation. environment and Planning B, 24, 165-174.

D'ambrosio, D., Di Gregorio, S., Gabriele, S., & Gaudio, R. (2001). A cellular automata model for soil erosion by water. Physics and Chemistry of the Earth, Part B: Hydrology, Oceans and Atmosphere, 26(1), 33-39.

De Almeida, C. M., Batty, M., Monteiro, A. M. V., Câmara, G., Soares-Filho, B. S., Cerqueira, G. C., & Pennachin, C. L. (2003). Stochastic cellular automata modeling of urban land use dynamics: empirical development and estimation. Computers, Environment and Urban Systems, 27(5), 481-509.

Deep, S., & Saklani, A. (2014). Urban sprawl modeling using cellular automata. The Egyptian Journal of Remote Sensing and Space Science, 17(2), 179-187.

Espínola, M., Ayala, R., Leguizamón, S., Iribarne, L., & Menenti, M. (2010). Cellular automata applied in remote sensing to implement contextual pseudo-fuzzy classification. In Cellular Automata (pp. 312-321). Springer Berlin Heidelberg.

Espinola, M., Piedra-Fernandez, J., Ayala, R., Iribarne, L., & Wang, J. Z. (2015). Contextual and Hierarchical Classification of Satellite Images Based on Cellular Automata. Geoscience and Remote Sensing, IEEE Transactions on, 53(2), 795-809.

Fathizad, H., Rostami, N., & Faramarzi, M. (2015). Detection and prediction of land cover changes using Markov chain model in semi-arid rangeland in western Iran. Environmental Monitoring and Assessment, 187(10), 1-12.

Feng, Y., Liu, Y., & Batty, M. (2015). Modeling urban growth with GIS based cellular automata and least squares SVM rules: a case study in Qingpu–Songjiang area of Shanghai, China. Stochastic Environmental Research and Risk Assessment, 1-14.

Fisher, P. (1997). The pixel: a snare and a delusion. International Journal of Remote Sensing, 18(3), 679-685.

Gong, W., Yuan, L., Fan, W., & Stott, P. (2015). Analysis and simulation of land use spatial pattern in Harbin prefecture based on trajectories and cellular automata—Markov modelling. International Journal of Applied Earth Observation and Geoinformation, 34, 207-216.

Guan, D., Li, H., Inohae, T., Su, W., Nagaie, T., & Hokao, K. (2011). Modeling urban land use change by the integration of cellular automaton and Markov model. Ecological Modelling, 222(20), 3761-3772.

Halmy, M. W. A., Gessler, P. E., Hicke, J. A., & Salem, B. B. (2015). Land use/land cover change detection and prediction in the north-western coastal desert of Egypt using Markov-CA. Applied Geography, 63, 101-112.

Han, J., Hayashi, Y., Cao, X., & Imura, H. (2009). Application of an integrated system dynamics and cellular automata model for urban growth assessment: A case study of Shanghai, China. Landscape and Urban Planning, 91(3), 133-141.

Harikrishnan, R. & Poongodi, S. (2015) Satellite image classification based on fuzzy with cellular automata. SSRG International Journal of Electronics and Communication Engineering, 2 (3), 137-141.

He, C., Okada, N., Zhang, Q., Shi, P., & Li, J. (2008). Modelling dynamic urban expansion processes incorporating a potential model with cellular automata. Landscape and urban planning, 86(1), 79-91.

He, C., Zhang, Q., Li, Y., Li, X., & Shi, P. (2005). Zoning grassland protection area using remote sensing and cellular automata modeling—a case study in Xilingol steppe grassland in northern China. Journal of Arid Environments, 63(4), 814-826.

He, Y., Ai, B., Yao, Y., & Zhong, F. (2015). Deriving urban dynamic evolution rules from self-adaptive cellular automata with multi-temporal remote sensing images. International Journal of Applied Earth Observation and Geoinformation, 38, 164-174.

Hegde, N. P., MuraliKrishna, I. V., & ChalapatiRao, K. V. (2007). Integration of cellular automata and GIS for simulating land use changes. Simulation, 1, 1-2.

Henriques, C., & Tenedório, J. A. (2009). Remote Sensing, GIS Application and Simulation of Coastal Land Use Changes Based on Cellular Automata: A Case Study of Maputo, Mozambique. Journal of Coastal Research, 56, 1518-1521.

Herold, M., Menz, G., & Clarke, K. C. (2001, June). Remote sensing and urban growth models—demands and perspectives. In Symposium on remote sensing of urban areas, Regensburg, Germany.

Houet, T., & Hubert-Moy, L. (2006). Modeling and projecting land-use and land-cover changes with Cellular Automaton in considering landscape trajectories. EARSeL eProceedings, 5(1), 63-76.

Huang, H. M., Zhang, L. Q., Guan, Y. J., & Wang, D. H. (2008). A cellular automata model for population expansion of Spartina alterniflora at Jiuduansha Shoals, Shanghai, China. Estuarine, Coastal and Shelf Science, 77(1), 47-55.

Huang, J., Wu, Y., Gao, T., Zhan, Y., & Cui, W. (2015). An Integrated Approach based on Markov Chain and Cellular Automata to Simulation of Urban Land Use Changes. *Appl. Math*, *9*(2), 769-775.

Huang, W., Liu, H., Luan, Q., Jiang, Q., Liu, J., & Liu, H. (2008). Detection and prediction of land use change in Beijing based on remote sensing and GIS. The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, 37, 75-82.

Kamusoko, C., Aniya, M., Adi, B., & Manjoro, M. (2009). Rural sustainability under threat in Zimbabwe–simulation of future land use/cover changes in the Bindura district based on the Markov-cellular automata model. Applied Geography, 29(3), 435-447.

Karafyllidis, I., & Thanailakis, A. (1997). A model for predicting forest fire spreading using cellular automata. Ecological Modelling, 99(1), 87-97.

Katiyar, S. K., & Arun, P. V. (2014). Cellular Automata based adaptive resampling technique for the processing of remotely sensed imagery. American Society for Photogrammetry and Remote Sensing, 79 2b, 182-193.

Khalilnia, M. H., Ghaemirad, T., & Abbaspour, R. A. (2013). Modeling of urban growth using cellular automata (CA) optimized by Particle Swarm Optimization (PSO). ISPRS-International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, 1(3), 231-234.

Kocabas, V., & Dragicevic, S. (2007). Enhancing a GIS cellular automata model of land use change: Bayesian networks, influence diagrams and causality. Transactions in GIS, 11(5), 681-702.

Köninger, A., & Bartel, S. (1997). 3D-GIS for urban planning–object hierarchy, methods and interactivity. Proceedings of JEC-GI, 97.

Leguizamón, S. (2006). Modeling land features dynamics by using cellular automata techniques. Proceedings of the ISPR Technical Comision, 7, 497-501.

Li, X., & Gar-On Yeh, A. (2004). Data mining of cellular automata's transition rules. International Journal of Geographical Information Science, 18(8), 723-744.

Li, X., & Yeh, A. G. O. (2000). Modelling sustainable urban development by the integration of constrained cellular automata and GIS. International Journal of Geographical Information Science, 14(2), 131-152.

Li, X., & Yeh, A. G. O. (2001). Calibration of cellular automata by using neural networks for the simulation of complex urban systems. Environment and Planning A, 33(8), 1445-1462.

Li, X., & Yeh, A. G. O. (2002). Urban simulation using principal components analysis and cellular automata for land-use planning. Photogrammetric engineering and remote sensing, 68(4), 341-352.

Li, X., Yang, Q., & Liu, X. (2008). Discovering and evaluating urban signatures for simulating compact development using cellular automata. Landscape and Urban Planning, 86(2), 177-186.

Liu, X., Li, X., Shi, X., Wu, S., & Liu, T. (2008). Simulating complex urban development using kernel-based non-linear cellular automata. Ecological modelling, 211(1), 169-181.

Liu, X., Li, X., Shi, X., Zhang, X., & Chen, Y. (2010). Simulating land-use dynamics under planning policies by integrating artificial immune systems with cellular automata. International Journal of Geographical Information Science, 24(5), 783-802.

Liu, Y., & Phinn, S. R. (2003). Modelling urban development with cellular automata incorporating fuzzy-set approaches. Computers, Environment and Urban Systems, 27(6), 637-658.

Liu, Y., Dai, L., & Xiong, H. (2015). Simulation of urban expansion patterns by integrating auto-logistic regression, Markov chain and cellular automata models. Journal of Environmental Planning and Management, 58(6), 1113-1136.

Lloret, J.R., Omtzigt, N., Koomen, E., & De Blois, F. S. (2008). 3D visualisations in simulations of future land use: exploring the possibilities of new, standard visualisation tools. International Journal of Digital Earth, 1(1), 148-154.

Louca, M., Vogiatzakis, I. N., & Moustakas, A. (2015). Modelling the combined effects of land use and climatic changes: coupling bioclimatic modelling with markov-chain cellular automata in a case study in Cyprus. Ecological Informatics (in press).

Luo, G., Amuti, T., Zhu, L., Mambetov, B. T., Maisupova, B., & Zhang, C. (2015). Dynamics of landscape patterns in an inland river delta of Central Asia based on a cellular automata-Markov model. Regional Environmental Change, 15(2), 277-289.

Maithani, S. (2010). Application of cellular automata and GIS techniques in urban growth modelling: A new perspective. Institute of Town Planners, India Journal, 7(1), 36-49.

Maithani, S. (2010). Cellular automata based model of urban spatial growth. Journal of the Indian Society of Remote Sensing, 38(4), 604-610.

Megahed, Y., Cabral, P., Silva, J., & Caetano, M. (2015). Land Cover Mapping Analysis and Urban Growth Modelling Using Remote Sensing Techniques in Greater Cairo Region—Egypt. ISPRS International Journal of Geo-Information, 4(3), 1750-1769.

Memarian, H., Balasundram, S. K., Talib, J. B., Sung, C. T. B., Sood, A. M., & Abbaspour, K. (2012). Validation of CA-Markov for simulation of land use and cover change in the Langat Basin, Malaysia.

Moghadam, H. S., & Helbich, M. (2013). Spatiotemporal urbanization processes in the megacity of Mumbai, India: a Markov chains-cellular automata urban growth model. Applied Geography, 40, 140-149.

Mubea, K., Goetzke, R., & Menz, G. (2014). Applying cellular automata for simulating and assessing urban growth scenario based in Nairobi, Kenya. International Journal of Advanced Computer Science and Applications, 5(2), 1-13.

Mundia, C. N., & Aniya, M. (2005). Analysis of land use/cover changes and urban expansion of Nairobi city using remote sensing and GIS. International Journal of Remote Sensing, 26(13), 2831-2849.

Munshi, T., Zuidgeest, M., Brussel, M., & van Maarseveen, M. (2014). Logistic regression and cellular automata-based modelling of retail, commercial and residential development in the city of Ahmedabad, India. Cities, 39, 68-86.

Nadoushan, M. A., Soffianian, A., & Alebrahim, A. (2015). Modeling Land Use/Cover Changes by the Combination of Markov Chain and Cellular Automata Markov (CA-Markov) Models. Journal of Earth, Environment and Health Sciences, 1(1), 16.

Nouri, J., Gharagozlou, A., Arjmandi, R., Faryadi, S., & Adl, M. (2014). Predicting Urban Land Use Changes Using a CA–Markov Model. Arabian Journal for Science and Engineering, 39(7), 5565-5573.

Olmedo, M. T. C., Pontius, R. G., Paegelow, M., & Mas, J. F. (2015). Comparison of simulation models in terms of quantity and allocation of land change. Environmental Modelling & Software, 69, 214-221.

Omar, N. Q., Ahamad, M. S. S., Hussin, W. M. A. W., Samat, N., & Ahmad, S. Z. B. (2014). Markov CA, multi regression, and multiple decision making for modeling historical changes in Kirkuk City, Iraq. Journal of the Indian Society of Remote Sensing, 42(1), 165-178.

Pan, Y., Roth, A., Yu, Z., & Doluschitz, R. (2010). The impact of variation in scale on the behavior of a cellular automata used for land use change modeling. Computers, Environment and Urban Systems, 34(5), 400-408.

Pinto, N. N. (2010). A cellular automata model based on irregular cells: application to small urban areas. Environment and Planning B: Planning and Design, 37(6), 1095-1114.

Poyil, R. P., & Misra, A. K. (2015). Urban agglomeration impact analysis using remote sensing and GIS techniques in Malegaon city, India. *International Journal of Sustainable Built Environment*.

Rabbani, A., Aghababaee, H., & Rajabi, M. A. (2012). Modeling dynamic urban growth using hybrid cellular automata and particle swarm optimization. Journal of Applied Remote Sensing, 6(1), 063582-1.

Sang, L., Zhang, C., Yang, J., Zhu, D., & Yun, W. (2011). Simulation of land use spatial pattern of towns and villages based on CA–Markov model. Mathematical and Computer Modelling, 54(3), 938-943.

Santé, I., García, A. M., Miranda, D., & Crecente, R. (2010). Cellular automata models for the simulation of real-world urban processes: A review and analysis. Landscape and Urban Planning, 96(2), 108-122.

Shiode, N. (2000). 3D urban models: recent developments in the digital modelling of urban environments in three-dimensions. GeoJournal, 52(3), 263-269

Sietchiping, R. (2004). A geographic information systems and cellular automata-based model of informal settlement growth.

Singh, A. K. (2003). Modelling land use land cover changes using cellular automata in a geo-spatial environment. International Institute for Geo-Information Science and Earth Observation. Thesis submitted for Master of Science, Enscheda, the Netherlands.

Singh, S. K., Mustak, S., Srivastava, P. K., Szabó, S., & Islam, T. (2015). Predicting Spatial and Decadal LULC Changes Through Cellular Automata Markov Chain Models Using Earth Observation Datasets and Geo-information. Environmental Processes, 2(1), 61-78.

Soares-Filho, B. S., Cerqueira, G. C., & Pennachin, C. L. (2002). DINAMICA—a stochastic cellular automata model designed to simulate the landscape dynamics in an Amazonian colonization frontier. Ecological modelling, 154(3), 217-235.

Sudhira, H. S., Ramachandra, T. V., & Jagadish, K. S. (2004). Urban sprawl: metrics, dynamics and modelling using GIS. International Journal of Applied Earth Observation and Geoinformation, 5(1), 29-39.

Takeyama, M., & Couclelis, H. (1997). Map dynamics: integrating cellular automata and GIS through Geo-Algebra. International Journal of Geographical Information Science, 11(1), 73-91.

Wagner, D. F. (1997). Cellular automata and geographic information systems. Environment and planning B, 24, 219-234.

Wang, F. (2012). A Cellular Automata Model to Simulate Land-use Changes at Fine Spatial Resolution.

Wang, S. Q., Zheng, X. Q., & Zang, X. B. (2012). Accuracy assessments of land use change simulation based on Markov-cellular automata model. Procedia Environmental Sciences, 13, 1238-1245.

Ward, D., Phinn, S. R., & Murray, A. T. (2000). Monitoring growth in rapidly urbanizing areas using remotely sensed data. The Professional Geographer, 52(3), 371-386.

Weng, Q. (2002). Land use change analysis in the Zhujiang Delta of China using satellite remote sensing, GIS and stochastic modelling. Journal of environmental management, 64(3), 273-284.

Wu, F. (1998). Simulating urban encroachment on rural land with fuzzy-logic-controlled cellular automata in a geographical information system. Journal of Environmental Management, 53(4), 293-308.

Wu, F. (2002). Calibration of stochastic cellular automata: the application to rural-urban land conversions. International Journal of Geographical Information Science, 16(8), 795-818.

Xu, C. H. E. N., Shi-Xiao, Y. U., & ZHANG, Y. P. (2013). Evaluation of spatiotemporal dynamics of simulated land use/cover in China using a probabilistic cellular automata-Markov Model. Pedosphere, 23(2), 243-255.

Yagoub, M. M., & Al Bizreh, A. A. (2014). Prediction of land cover change using Markov and cellular automata models: case of Al-Ain, UAE, 1992-2030. Journal of the Indian Society of Remote Sensing, 42(3), 665-671.

Yang, X., Zheng, X. Q., & Chen, R. (2014). A land use change model: Integrating landscape pattern indexes and Markov-CA. Ecological Modelling, 283, 1-7.

Yang, X., Zheng, X. Q., & Lv, L. N. (2012). A spatiotemporal model of land use change based on ant colony optimization, Markov chain and cellular automata. Ecological Modelling, 233, 11-19.

Yang, Y., Zhang, S., Yang, J., Xing, X., & Wang, D. (2015). Using a Cellular Automata-Markov Model to Reconstruct Spatial Land-Use Patterns in Zhenlai County, Northeast China. Energies, 8(5), 3882-3902.

Ye, B., & Bai, Z. (2008). Simulating land use/cover changes of Nenjiang County based on CA-Markov model. In Computer and Computing Technologies In Agriculture, Volume I (pp. 321-329). Springer US.

Yeh, A. G. O., & Li, X. (2001). A constrained CA model for the simulation and planning of sustainable urban forms by using GIS. *Environment and Planning B: Planning and Design*, *28*(5), 733-753.

Yeh, A. G. O., & Li, X. (2002). A cellular automata model to simulate development density for urban planning. Environment and Planning B, 29(3), 431-450.

Yeh, A. G. O., & Li, X. (2006). Errors and uncertainties in urban cellular automata. Computers, Environment and Urban Systems, 30(1), 10-28.

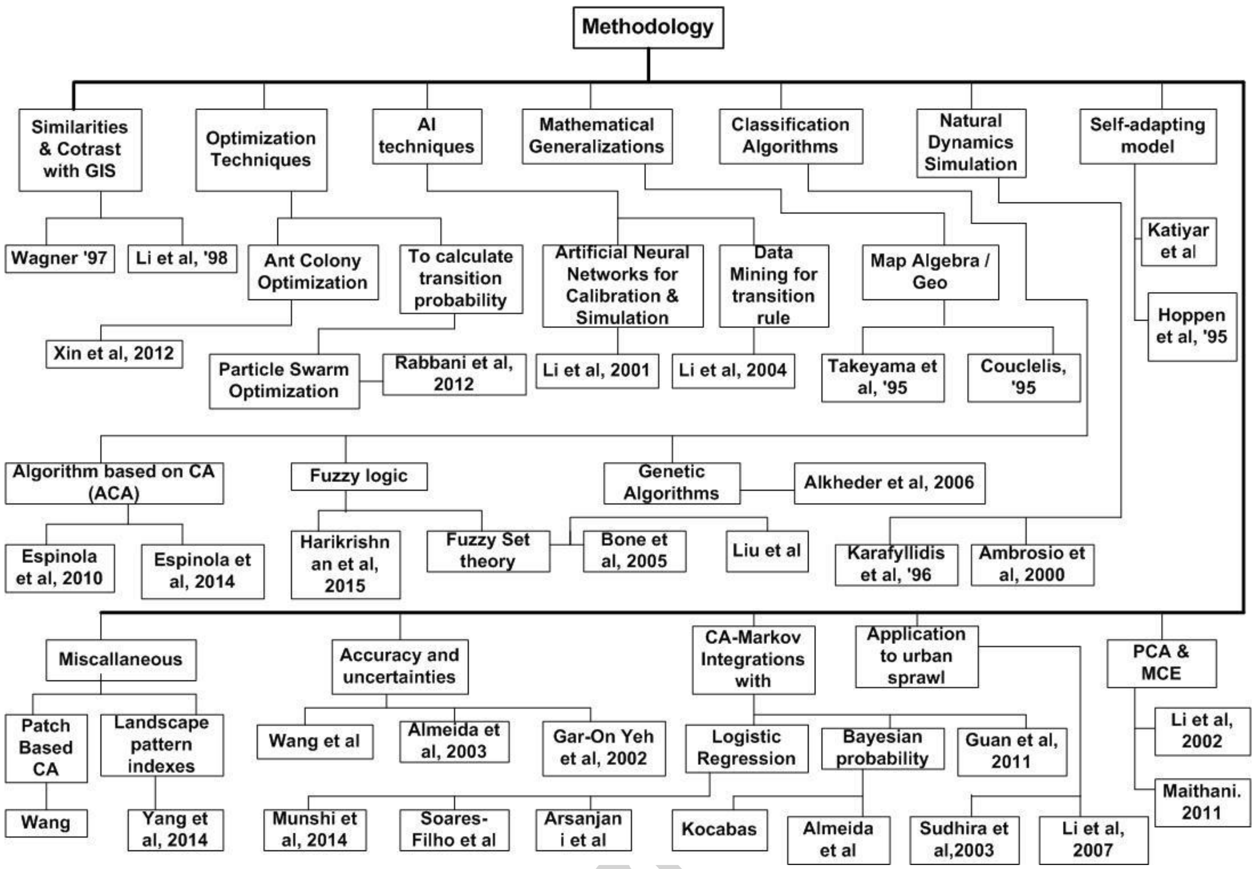
Zhou, D., Lin, Z., & Liu, L. (2012). Regional land salinization assessment and simulation through cellular automaton-Markov modeling and spatial pattern analysis. Science of the total environment, 439, 260-274.

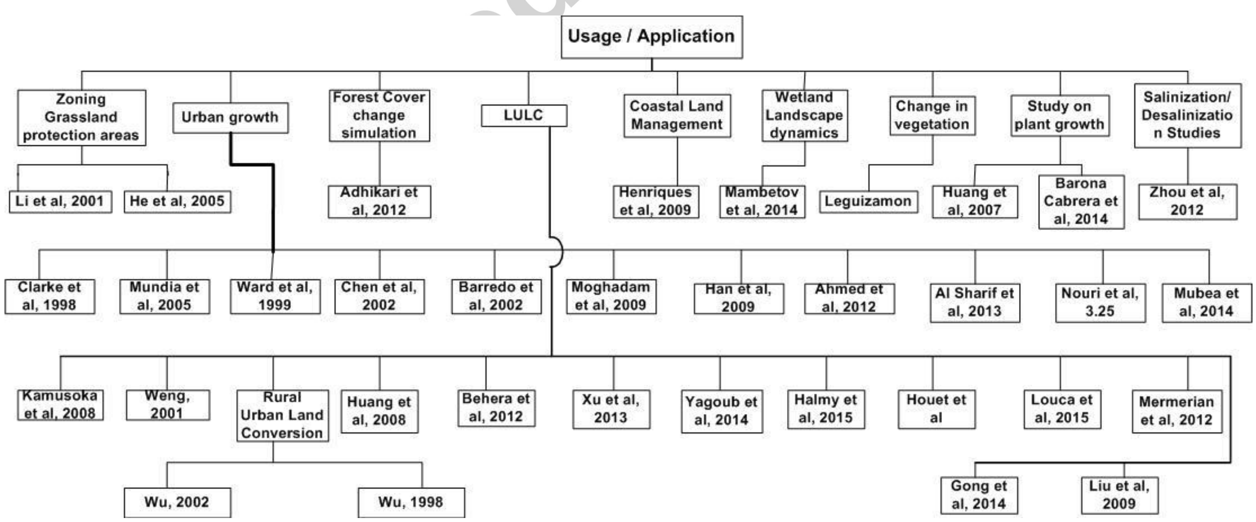
Fig 1. Methodological developments in CA-Markov Chain in geospatial environmental modelling.

Fig 2. Usage and applications of CA-Markov Chain in geospatial environmental modelling.

Highlights

- CA-Markov approach becoming inevitable in the field of predictive geospatial modeling
- Fuzzy logic, neural networks & CA-Markov : an unexplored combination with potential
- Linking extreme events & socioeconomic factors to CA-Markov modeling needs emphasis
- Self-adapting CA in Map algebra framework: a goldmine for future studies


Methodology
Similarities & Cotrast with GIS
Optimization Techniques
AI techniques
Mathematical Generalizations
Classification Algorithms
Natural Dynamics Simulation
Self-adapting model
Wagner '97
Li et al, '98
Ant Colony Optimization
To calculate transition probability
Artificial Neural Networks for Calibration & Simulation
Data Mining for transition rule
Map Algebra / Geo
Katiyar et al
Hoppen et al, '95
Xin et al, 2012
Particle Swarm Optimization
Rabbani et al, 2012
Li et al, 2001
Li et al, 2004
Takeyama et al, '95
Couclelis, '95
Algorithm based on CA (ACA)
Fuzzy logic
Genetic Algorithms
Alkheder et al, 2006
Espinola et al, 2010
Espinola et al, 2014
Harikrishnan et al, 2015
Fuzzy Set theory
Bone et al, 2005
Liu et al
Karafyllidis et al, '96
Ambrosio et al, 2000
Miscallaneous
Accuracy and uncertainties
CA-Markov Integrations with
Application to urban sprawl
PCA & MCE
Patch Based CA
Landscape pattern indexes
Wang et al
Almeida et al, 2003
Gar-On Yeh et al, 2002
Logistic Regression
Bayesian probability
Guan et al, 2011
Li et al, 2002
Maithani. 2011
Wang
Yang et al, 2014
Munshi et al, 2014
Soares-Filho et al
Arsanjani et al
Kocabas
Almeida et al
Sudhira et al,2003
Li et al, 2007


Usage / Application
Zoning Grassland protection areas
Urban growth
Forest Cover change simulation
LULC
Coastal Land Management
Wetland Landscape dynamics
Change in vegetation
Study on plant growth
Salinization/ Desalinization Studies
Li et al, 2001
He et al, 2005
Adhikari et al, 2012
Henriques et al, 2009
Mambetov et al, 2014
Leguizamon
Huang et al, 2007
Barona Cabrera et al, 2014
Zhou et al, 2012
Clarke et al, 1998
Mundia et al, 2005
Ward et al, 1999
Chen et al, 2002
Barredo et al, 2002
Moghadam et al, 2009
Han et al, 2009
Ahmed et al, 2012
Al Sharif et al, 2013
Nouri et al, 3.25
Mubea et al, 2014
Kamusoka et al, 2008
Weng, 2001
Rural Urban Land Conversion
Huang et al, 2008
Behera et al, 2012
Xu et al, 2013
Yagoub et al, 2014
Halmy et al, 2015
Houet et al
Louca et al, 2015
Mermerian et al, 2012
Wu, 2002
Wu, 1998
Gong et al, 2014
Liu et al, 2009