### Chapter 4: Cellular Automata Model

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4.1 Introduction

The rapid growth of urban areas raises important issues to modern societies in general and to the planning processes in particular. Sustainable development is now the key driver of urban growth imposing detailed scrutiny of trends, strategies, and public policies that are aimed to shape desirable futures. The complexity of these problems is such that there are no direct ways to achieve a solution nor these solutions are based on a single approach. On the one hand the consideration of different inputs – physical, sociological, economic, and historical, among several others – gives the comprehensive planning process, the necessary tools to tackle complexity. On the other hand, this high level of complexity can be a potential weakness, because the problems become increasingly more complex as the natural evolution of societies takes place, demanding from planners new levels of commitment and accuracy in their research and practice. This knowledge can be used to develop models that aim to explain urban phenomena, retain knowledge from urban systems, and forecast planning scenarios. The study presented focus on the application of a cellular automata (CA) model to simulate urban change in the Metropolitan Area of Bangalore. CA models are a matter of intensive research since the late 1980s when information systems were making their entrance on the field of geography. After the introduction of CA to geography by Waldo Tobler (1979), a period of theoretical development took place and the first applications of CA to both theoretical instances and to real world case studies were made (Couclelis, 1985, 1987, White and Engelen, 1993, Batty and Xie, 1994). Since then, numerous variations and improvements were made and CA is widely used for simulating increasingly more complex problems (Wu and Webster, 1998, O'Sullivan, 2001a, Silva and Clarke, 2002, Barreto et al., 2003, Ward et al., 2003, Liu et al., 2008). However, the larger majority of these applications were made considering regular cells, often derived from remote sense imagery. There is only a small group of studies that developed CA models considering irregular cellular fabrics (Semboloni, 2000, O'Sullivan, 2001b, Pinto, 2006, Stevens et al., 2007). This particular characteristic is of great importance for the simulation of local scale problems, where the traditional regular cell, obtained from satellite images, may not represent well the spatial structure of the territory.

The review of the GIS approach has indicated that it does not have a dynamic modelling capacity. To achieve this thesis’ aim of developing a realistic urban dynamic model, especially an IS growth model, it will be useful to seek the contribution of dynamic models that will supplement spatial models (such as GIS). Cellular automata (CA) are becoming increasingly used
as urban modelling tools mostly because they are simple to build, flexible to formulate, and capable of generating complex patterns that can emerge from historical evolution trends through the diffusion process. Cellular automata, thus, appears to comprise a plausible additional conceptual framework able to complement the GIS ability to manage IS factors. Specifically, CA can assist the development of the simulation and prediction component of the proposed IS growth model, which can only be performed within a current GIS framework. This section will discuss the concept of CA and its theoretical formulation, and then present some examples of CA applications as an exploration of hypothetical urban modelling. It will finally present some examples and attempts at modelling real urban dynamics using CA.

4.2 Concept of CA

Cellular automata are mathematical idealizations of physical systems in which space and time are discrete, and physical quantities take on a finite set of discrete values. A cellular automaton consists of a regular uniform lattice (or "array"), usually infinite in extent, with a discrete variable at each site ("cell"). The state of a cellular automaton is completely specified by the values of the variables at each site. A cellular automaton evolves in discrete time steps, with the value of the variable at one site being affected by the values of variables at sites in its "neighborhood" on the previous time step. The neighborhood of a site is typically taken to be the site itself and all immediately adjacent sites. The variables at each site are updated simultaneously ("synchronously"), based on the values of the variables in their neighborhood at the preceding time step, and according to a definite set of "local rules."

Cellular automata were originally introduced by von Neumann and Ulam (under the name of "cellular spaces") as a possible idealization of biological systems (von Neumann, 1963, 1966), with the particular purpose of modelling biological self-reproduction. They are applied and reintroduced for a wide variety of purposes, and referred by variety of names, including "tessellation automata," "homogeneous structures," "cellular structures," "tessellation structures," and "iterative arrays."

Thus, a cellular space qualifies the basic component of the space, while an automaton is a self-organizing element that performs logical and continuous programmable instructions. The concept of a self-organizing system is central in CA urban dynamics modelling and it refers to the tendency for system structures to spontaneously develop ordered patterns, often on a large
scale (Torrens, 2000; 2001). In its original format, CA can be understood as a mathematical idealization of physical and dynamic systems in which space and time are discrete, and physical quantities take on a finite set of discrete values (Semboloni, 2000). A cellular automaton consists of five main elements:

- A regular uniform and infinite 'lattice' or 'array' with discrete variables at each cell, (e.g., an urban space). Lattice space has $n$ dimensions, but two-dimensional CA is the most common in urban dynamics simulation. Few urban studies have used three-dimensional CA.

  **Diagram 4.1**: One dimensional CA grid with three neighbors on lattice of 7 cells

- A 'cell' is a subunit of a regular geometrical grid. While usually in a rectangular grid, a cell can be formulated as an irregular polygon, hexagon or a link. A cell (or a site) is a single element in the entire lattice (space). During the simulation (or the changing of state), cells react on the entire lattice, observing the same transition rules. Although representing only one state at the time, a cell encapsulates an infinite number of states variable, a geographical location and various attributes.

- A 'state' is a variable, which takes a different value at each site or time. It can be a property, a number or word (0 or 1, urban or non-urban). It can vary from two (Conway) to 29 (Von Neumann). The variables at each site are updated synchronously.

- The 'neighborhoods'. In a grid, these are normally the cells physically closest to the central cell which might influence its value at the next step. During the simulation, neighborhood cells act as immediate areas of interest or zones of impact for the central cell. The neighborhood includes the cell itself.

  **Diagram 4.2**: Two dimensional Von Neumann 5 neighbour
  **Diagram 4.3**: Two dimensional Moore neighbourhood grid cells, 7^2 possible cell states
  **Diagram 4.4**: Extended Moore neighbourhoods

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• Local or transitional 'rules' are a set of conditions or functions that define how each cell’s state changes in response to its current state and that of its neighbors. The future state of cells is determined by the transitional rules in a discrete time frame.

Other properties of CA include animation and dynamic visualization. CA behaves in accordance with the principle of 'think locally, act globally'. That is, it can encapsulate specific and smaller details that define the bigger picture. In relation to informal settlements modelling, CA will assist in developing a model that shows how the combination of different factors of IS emergence and growth interact and contribute to the future expansion of IS. As a 'bottom-up' approach, CA applications pay particular attention to detail and are spatially and temporally explicit. This capacity to integrate spatial and temporal dimensions makes CA appealing for the development of robust and reliable urban dynamics models. The urban dynamics modelling proposed for the development in this thesis has, therefore, many reasons to use CA to correct the weaknesses of traditional urban dynamics modelling. The potential for integrating CA with spatial technologies, such as GIS, opens up new possibilities to improve operational urban modelling, particularly with regard to the prediction of dynamic visualization of informal settlement emergence and growth.

The simulation of urban dynamics is an area of research where CA has been recently implemented. Here, cellular automata represent a useful tool for understanding urban dynamics, improving theory, achieving realistic and operational urban models (White, 1998). White and Engelen (1993) have demonstrated that a cellular automata approach can lead to a better understanding of spatial patterns, as well as representing realistic patterns. In the spatial modelling perspective, the strengths of CA lie in their capacity to perform dynamic spatial modelling over a discrete and continuous Euclidean space. Similarly, CA had the ability to exhibit explicit spatio-temporal dynamics. Other work has shown how CA models can be integrated with other spatio-temporal models, to improve the representation of urban features (Bertuglia et al., 1990; Bivand & Lucas, 2000; Openshaw & Abrahart, 2000). Finally, the flexibility of transitional rules embedded into CA architecture favors a better 'control' over the dynamic patterns that are generated. The important role of using complex systems such as cellular automata to seek to discover, understand and explain how cities emerge and change is now well established (Couclelis, 1985; White & Engelen, 1994; Allen, 1997; 1999; Portugali, 2000).
One of the most significant improvements to CA models comes from Wu’s work. Wu (1998a) applied CA in a generic city to highlight the fact that CA can significantly improve the understanding of growth patterns of polycentric urban forms. Wu and Webster (1998) also applied CA to explore the sustainability of urban forms. Two main difficulties have, however, limited these experimentations into real urban areas. First, the limited size of the space considered by CA software reduces the potentiality of these applications in real world situations. In addition, many of these applications are limited to 'two-state' behavior, such as urban/non-urban, whereas urban systems can embed several states at the same time (Batty, 2000). Second, real-world applications of Wu’s model were limited due to difficulties experienced in spatially reflecting some fundamental formulations of CA. For example, the model did not address the concept of CA explicit representation of change of state based on general rules and attributes of the neighbouring elements. Likewise, the model failed to clarify the CA principle that global change is generated by local behavior. In light of these key questions, researchers who are concerned about realistic representation have therefore had to readjust the fundamental structure and behavior of CA, or seek alternative integration with other spatial models that can better handle real world data.

4.3 Cellular Automata Characterization

Conceptually and theoretically, a cellular automaton for urban studies has some limitations and advantages with regard to the development of an urban dynamics framework. This section first discusses some of the limitations of CA and how they can be overcome, and then expands on CA’s strengths to improve 'real-world' simulation and modelling.

The original framework of CA is not appropriate to inform and support realistic urban dynamics (Wolfram, 1986). For instance, the overall original structure of CA is reported to have been too simplistic and constrained to apply in real urban applications (Sipper, 1997). Specifically, the original concept of cells as 'systems closure' is not considered suitable for urban dynamics studies because not all spatial patterns have a regular grid form (Batty & Torrens, 2001). Similarly, it is not reasonable to apply the idea of an infinite space plane (two-dimensional) and uniform regular space to the city because cities are not infinite, regular, or uniform. Moreover, the notion of neighborhood is too coarse and does not take external factors and distance-decay actions into consideration.
Another criticism is that cellular automata only take a bottom-up approach, and account for local specificities that ultimately define the overall representation of the space generally. All constituents of urban systems, however, do not exhibit only bottom-up behavior (e.g., urban planning decisions, national policies, macro-economy, and so on). Furthermore, CA is restricted to general rules and does not create its own dynamic. In real urban contexts, not all changes in the systems are driven by the same force or mechanism. It is clear that urban elements can react differently to general rules. However, these apparent rigidities of original CA architecture can be progressively turned into strengths to develop comprehensive models, especially when associated with other spatial tools.

Cellular automata were initially used to investigate emergent, complex and adaptive behavior, especially self-organizing systems (Wolfram, 1984). Applied in urban dynamics studies, the CA framework is continuously amended and relaxed to generate realistic patterns. In the original CA, transition rules are universal and applied synchronically to all cells. In real urban processes and forms, however, no single rule governs the behavior of the entire system. To solve the rigid transitional rules, urban dynamics CA transition rules are formulated using Boolean statements, and probabilistic expressions such as IF, THEN and ELSE. The flexibility thus gained in these expressions, simplifies the representation of more complex systems (Batty, 1996).

Turning to strength, the simulation of urban dynamics is an area of research where CA has been recently implemented. Here, CA represents a useful tool for understanding urban dynamics, improving theory, achieving realistic and operational urban models (White, 1998). White and Engelen (1993) have demonstrated that a cellular automata approach can lead to a better understanding of spatial patterns as well as representing realistic patterns. In the spatial modelling perspective, the strengths of CA lie in their capacity to perform dynamic spatial modelling over a discrete and continuous Euclidean space. Similarly, CA has the ability to exhibit explicit spatio-temporal dynamics. Several studies (For example Bivand and Lucas, 2000; Openshaw and Abrahart, 2000) have shown how CA models can be integrated with other spatio-temporal models to improve the representation of urban features. Finally, the flexibility of transitional rules embedded into CA architecture favors an effective control over the dynamic patterns that are generated. Role of CA is to discover, understand and explain how cities emerge and change (Couclelis, 1985; White and Engelen, 1994; Portugali, 2000; Ward et al., 2000).
4.4 Application of CA in Peri-urban Studies

The periurbanisation concept: There are many concepts that are used to describe urban change in the literature, but some of them seem to dominate the debate in Europe: suburbanization is the most widespread; counter-urbanization is also very common, while periurbanisation is more and more common in the French-speaking literature (and in Southern Europe case studies). We have chosen to use the periurban concept throughout the thesis because its general understanding in the literature is closely related to the spatial characteristics that we want to analyze, and also because there is some sort of consensus about its sense.

We choose to define periurban areas according to the following two characteristics:

(i) Periurban areas under urban influence. The nature of the link between the periurban zone and the centre is functional and is characterized by commuting flows.

(ii) Periurban areas show rural character due to the presence of an agro-forestry sector which represents an important part of the total surface and implies low population densities.

The rural aspect of periurban zones is probably one of the main differences between the suburban and the periurban concepts. In our understanding, the former appears more agglomerated or dense. In fact, some authors differentiate suburban from periurban (often more distant from the city) in the same study, while others do not (Vandermotten, 1991). The differentiating criteria can be, for example, the commuting mode: individual car for periurbanisation and public transport for suburbanization (Halleux, 2001). The periurban concept is neither comparable with the counter-urbanization Concept, which deals with change in the urban hierarchy due to migration flows toward medium and small-sized cities. This phenomenon, therefore, occurs at a different scale than periurbanisation by considering the whole urban network rather than a single functional region. It has however been doubted whether counter-urbanization is a separate concept of suburbanization (Nelson and Sanchez, 1999).

Challenges facing cellular models: For all of their advantages, applications, and uses in urban geosimulation, cellular automata modeling of peri-urban systems is still very much in its infancy. Indeed, there are early indications that the framework has some serious challenges facing it, particularly if cellular models are to step out of the realm of abstract academic experimentation and into the world of operational scenario simulation, planning support, and urban management. Key difficulties already apparent include issues of cellular model calibration,
their capacity to represent top-down processes, the meaning of transition rules and their match with theoretical knowledge of how we understand urban systems, as well as the ramifications of tinkering with the formalism that works so well for many closed physical systems.

Cellular Automata is one of the applications what we can apply for the Peri-urban studies. When you are applying imagers or raster formats each and every cell having the values, and that value is compared with the nearest neighbor cell values. Applying the cellular automata model we can differentiate the object available on each cell, for every object we are assigning the transition rules and continue the research on the basis of the temporal changes. In the peri-urban areas the cells values will be different from the values available in the urban and rural areas.

4.5 Classic C A Structure – Cells, Neighborhood, Transition Rules, Time

A cellular automation consists of a grid of cells distributed normally in a matrix form that has the following basic features

Working principle: The CA model in general works by

• Simulating the present by extrapolating from the past using the image time-series,
• Validating the simulations via the remotely sensed time-series of past conditions and through the available collection of field observations,
• Allowing the model to iterate to the year of choice in future and
• Comparing model outputs to an autoregressive time-series approach for annual conditions

Urban Modeling: The formalism described in the first section adapted to meet the needs of urban researchers in several ways:

Cell space: Of course, the idea of an infinite spatial plain is unrealistic in an urban context. Cellular automata are therefore constrained in their cell space to finite dimensions. The regularity of this space is also questionable in urban contexts. Some cities are quite regular in their structure (at least from the perspective of block configuration, say, in a city like Manhattan), but most are markedly irregular, e.g., cities such as Dublin, Athens, Venice, etc. Recent research has adapted the structure of cellular automata spaces and rendered them irregular.

Cell states: In the traditional cellular automation, cell states are discrete (and quite often binary): alive or dead, one or zero. There is little in the city, however, that is discrete. Most conditions--land use, land value, land coverage, demographic mix, density, etc.--are continuous, and of course urban spaces are multi-faceted. Therefore, cellular models of urban systems
commonly contain several cell states simultaneously, and these states range in type from absolute to discrete and to continuous. An innovative adaptation to the traditional idea of the cell state is the introduction of fixed (states that cannot be altered by transition rules) and unfixed cell states, corresponding respectively, for example, to water sites or land values.

**Neighborhoods:** The idea of the neighborhood in the formal cellular automation is rather restrictive. Urban neighborhoods come in many shapes, configurations, and sizes. Complaining that neighborhoods such as the Moore and von Neumann restrict the level of spatial variation that cellular automata models can generate, many researchers have tinkered with neighborhoods to include the notion of 'action-at-a-distance'. Cell neighborhoods consisting of 113 cells have in some cases been used in simulations.

**Transition rules:** Perhaps the greatest tinkering with cellular automata models comes in the formulation of the transition rules. It is here that cellular models of urban systems are generated with adherence to what we know in theory about cities. Recently, urban studies using cellular models have introduced an innovative range of parameters into transition rules in a bid to enhance their realism. These parameters have included probabilistic functions, utility-maximization, accessibility calculations, exogenous links and constraints (linking cellular models to other models), weights, hierarchies, inertia, and stochasticity.

**Discrete Time:** Discrete time is abstract in standard CA. It is corresponding to a certain time point of CA model running only. Therefore, how to match the abstract time to a material date is very important during the process of simulating geography phenomenon using VCA (Vector Cellular Automata). Generally, there are two methods as follows: 1) Ratiocinating using data. We can make use of a series of history data to train the VCA, ratiocinate the actual time by analyzing the simulating result and the history data. 2) Combination of VCA and other model. Firstly, other forecasting models such as regression analysis, gray forecasting, Markov Process and differential equation and so on are used to forecast a certain geographical phenomenon, then we compare the forecasting results with the result of VCA simulating, find the relation of both, and ratiocinate the actual time (Zhou et al., 2001).

When we work with satellite images, we consider each pixel of the image as a cell of the cellular automation and we normally take the 8 around pixels as neighborhood (Moore Neighborhood), although we can take the 4 around pixels (von Neumann Neighborhood) or even the 24 around pixels (Extended Moore Neighborhood). The changes in cells states occur in discrete time form. In each iteration the whole cells are checked and rules are applied through the transition function $f$ to each cell taking into account the around neighborhood to change its state.
Therefore cellular automata have an evolution process because the cells are always changing their states across the different iterations. From this point of view, in recent years cellular automata have become a powerful tool applied in remote sensing especially to simulate satellite images processes.

### 4.6 Markov Chain Principles

Most of our study of probability has dealt with independent trials processes. These processes are the basis of classical probability theory and much of statistics. We have discussed two of the principal theorems for these processes: the Law of Large Numbers and the Central Limit Theorem. We have seen that when a sequence of chance experiments forms an independent trials process, the possible outcomes for each experiment are the same and occur with the same probability. Further, knowledge of the outcomes of the previous experiments does not influence our predictions for the outcomes of the next experiment. The distribution for the outcomes of a single experiment is sufficient to construct a tree and a tree measure for a sequence of n experiments, and we can answer any probability question about these experiments by using this tree measure.

Modern probability theory studies chance processes for which the knowledge of previous outcomes influences predictions for future experiments. In principle, when we observe a sequence of chance experiments, all of the past outcomes could influence our predictions for the next experiment. For example, this should be the case in predicting a student's grades on a sequence of exams in a course. But to allow this much generality would make it very difficult to prove general results. In 1907, A. A. Markov began the study of an important new type of chance process. In this process, the outcome of a given experiment can affect the outcome of the next experiment. This type of process is called a Markov chain.

**Specifying a Markov Chain:** We describe a Markov chain as follows: We have a set of states, \( S = \{s_1; s_2; \ldots; s_r\} \). The process starts in one of these states and moves successively from one state to another. Each move is called a step. If the chain is currently in state \( s_i \), then it moves to state \( s_j \) at the next step with a probability denoted by \( p_{ij} \) and this probability does not depend upon which states the chain was in before the current state.
The probabilities $p_{ij}$ are called transition probabilities. The process can remain in the state it is in, and this occurs with probability $p_{ii}$. An initial probability distribution, defined on $S$, specifies the starting state. Usually this is done by specifying a particular state as the starting state. R. A. Howard provides us with a picturesque description of a Markov chain as a frog jumping on a set of lily pads. The frog starts on one of the pads and then jumps from lily pad to lily pad with the appropriate transition probabilities.

4.7 Fuzzy C A Models

Fuzzy Logic (FL) was originally proposed by Zadeh (1965) as a generalization of binary logic in order to model imprecision, vagueness and uncertainty in real world. There is a common fallacy that FL introduces uncertainty into the modeling process while in fact it provides the tools to model the inherent uncertainty that would otherwise be thrown out of the equation. In FL, as well as in binary logic, variables consist of sets. In many cases though the classical bimodal set membership function is unnecessarily restrictive (Heikkila et al. 2002) and so it is a good think that fuzzy logic does not comply with the binary property of dichotomy; as a result fuzzy variables may consist of partially overlapping fuzzy sets.

Cellular Automata (CA) is a computational methodology that has been applied to various science fields, such as numerical analysis, computational fluid dynamics, simulation of biological and ecological systems, traffic analysis, growth phenomena modeling, etc. In CA the system under study is divided into a set of cells with each cell interacting with all other cells belonging to predefined neighborhoods through a set of simple rules. The interactions take place in discrete time steps with each cell’s state at any time period estimated by considering the state of the neighboring cells. This approach is repeated continuously in a self-reproductive mechanism with no external interference. Growth is thus simulated through a bottom up approach and this makes CA an appropriate technique for simulating complex phenomena that is difficult to model with other approaches. There is a great variety of highly sophisticated crisp approaches concerning CA based urban growth modeling. Among them, the stochastic approach of Mulianat et al, the object-oriented approaches of Cage and Obeus, the approach proposed by Morshed, the environment Laude that combine CA and Genetic Algorithms and other widely applied models, such as Sleuth. These models are either quantitative or qualitative. Quantitative numerical models focus on the efficiency of the estimations and may provide accurate results. What such models are not capable of is to map and express the qualitative characteristics of
urban growth phenomenon, which are a result of the socio-economic decision making of the urban population. Qualitative rule-based models on the other hand are capable of such mapping and expression since they focus on the quality of causes and effects. Nevertheless, in the binary world of classical rule-based systems, qualities, objects and relations are strictly defined and they either exist or not. There is no such thing as partial, uncertain or imprecise fact, membership or relation and this is not the way it works in real world.

Fuzzy logic allows the continuous analysis between “false” and “true” and bridges the gap between qualitative and quantitative modeling. Fuzzy logic was originally proposed by Zadeh as a generalization of binary logic and is used to model imprecision, vagueness and uncertainty in real world. Fuzzy logic does not comply with the binary property of dichotomy; hence fuzzy variables may consist of partially overlapping fuzzy sets. When a fuzzy set is meant to manage quantitative (numerical) information, it is fully described by a membership function which returns a membership value (µ) within [0,1] for a given object in the fuzzy set. Otherwise we refer to them as fuzzy symbols. For each fuzzy set, a linguistic variable familiar to its quality is used. Linguistic variables, apart from describing primitive fuzzy sets, are also used to define new sets, based on the primitive ones. This is accomplished by applying fuzzy hedges which are verbal definitions, such as ‘more or less’, ’not’, ‘very’ etc. Each hedge is joined to a numerical expression which is applied to the membership function of the primitive set. Linguistics in fuzzy logic, allow the management of information in a way closer to this of human conceptualization.

The knowledge base is represented as “IF…THEN” rules, connecting hypotheses to conclusions through a certainty factor. The most frequently used inference engines are the Mamdani and the Sugeno approach. In the Mamdani approach, the inference engine is divided into the stages of aggregation, implication and accumulation [10][11]. Aggregation returns the fulfillment of hypothesis for every rule individually, A Fuzzy Cellular Automata Modeling Approach 143 implication combines aggregation’s result to the rule’s certainty factor (CF) resulting to the degree of fulfillment for each rule’s conclusion, while accumulation corresponds to compromising different individual conclusions into a final result. The Sugeno approach is very similar, the main difference being that the rule’s conclusion may either be a constant or a function of the rule’s hypothesis. In our case, fuzzy logic provides a proper framework for managing both qualitative and quantitative information and describing facts and relations using linguistic terms.
**Coupling Fuzzy Systems and Cellular Automata:** Combinations of CA and FL have only recently appeared in geographic applications and spatial modeling. Most of them are used to simulate the expansion of spatial or spatially referenced phenomena such as forest fire simulation, electricity load forecasting and urban growth modeling. Regarding the field of urban modeling there are approaches that use FL to calculate some of the CA parameters and approaches that apply fuzzy systems to simulate growth such as the theoretical approach proposed by Dragicevic.

**Wu's approach** – possibly the very first one – introduces fuzzy-logic control in CA to define the urban transition dynamics using transparent verbal multi-criteria like rules. This system has crisp input and output and uses basic CFR (max-min inference operators and hedges) to produce conditional scenarios in a gaming style. The major drawbacks in this approach are that time is measured in CA steps without being linked to the growth occurred and that while a fuzzy inference is applied, the output is described in crisp sets. Despite the remarkable achievements of previous approaches, their performance can be further improved in many aspects. The key concept in those approaches is familiar to the model we herein propose but there are many differences and technical advantages. We attempt to combine the advantages of previous models and eliminate some of their drawbacks while it introduces some new features as described in the following section.

**4.8 Software and CA Implementations**

Most current GIS techniques have limitations in modeling changes in the landscape overtime, but the integration of CA and GIS has demonstrated considerable potential. The limitations of contemporary GIS include, its poor ability to handle dynamic spatial models, poor handling of the temporal dimensions. In coupling GIS with CA, CA can serve as an analytical engine to provide flexible framework for the programming and running of dynamic spatial models. Masanao and Couclelis address a generalized modeling formalism of CA, which is extended with Geo-algebra capable of expressing a variety of dynamic spatial models within a common framework.

**Use of commercial GIS software:** Within this approach, there are two choices of developing spatial simulation models – loose-coupled integration or tight-coupled integration with GIS. If commercial GIS software meets the needs of building a simulation model, a tight-
coupled integration is the ideal solution. Under this situation, spatial simulation model will be represented in GIS macro language, such as Arc/Info AML, or Arcview Avenue. Takeyama and Couclelis (1997) developed the basic concepts of Geo-Algebra. Geo-Algebra is a mathematical generalization of map algebra, and capable of expressing a variety of dynamic spatial models and spatial data manipulations within a common framework. But Clarke (1998) stated that Geo-Algebra was not sufficient to represent a land use CA simulation model and suggested the more flexible approach – loose-coupled integration. When commercial GIS software could not handle the complexity of the spatial simulation model, and the model also requires some basic spatial data management, display and analysis, a loose-coupled approach usually is suggested. Loose-coupled integration develops the simulation model with C, C++, JAVA or other programming languages, and connects it with commercial GIS software. GIS saves the efforts to develop a spatial data view/analysis system.

**Role of GIS in CA based Modeling:** In order to be useful and realistic, urban models depend on real-world data such existing urban land uses and growth patterns, existing road network, location of various facilities, availability of infrastructure facilities etc. that can be integrated and mapped in a modeling scenario. Geographic Information Systems have emerged a prime framework for the integration and management of a range of spatial real world data. However, to use GIS alone as a modeling tool have been received with skepticism as it has limited modeling functionalities and has constraints in handling temporal data sets. Nevertheless, GIS and CA in combination can be used as a strong couple to model the urban growth to take advantages of both the techniques. For example, although the capacity of CA to explore complex systems has been well established (Itami, 1994), its capacity to represent real patterns is yet to be proven. In case of GIS, its spatial data analysis capacities may be insufficient to handle complex urban dynamics. The integration of the dynamic strength of CA with the effective spatial representation found in GIS thus may be beneficial to achieve realistic representation of a phenomenon such as urban growth.

A number of important points have been raised in the literature about the benefits of linking GIS and CA to improve urban dynamics modeling. GIS and CA have been argued to have significant common features and complementary functionalities, and can therefore supplement and complement each other. Couclelis discussed the theoretical considerations for the integration of GIS and CA as well as their potentialities in improving the quality of spatial urban dynamics models. Couclelis also pointed out the natural affinity between CA and GIS and
advocated more interactive and visual integration of GIS and CA to improve the patterns of realism in urban modeling and simulation. In many ways, the deficiencies of GIS and CA can be compensated by each other. For example, although the capacity of CA to explore complex systems is well established, its capacity to represent real patterns has still to be proven. In case of GIS, its predictive and analytical capacities are insufficient to handle complex urban dynamics. The integration of the dynamic strength of CA with the realistic temporal and spatial representation found in GIS and remote sensing is, therefore, appealing as a practical means to achieve realistic representation. On one hand, GIS has much to offer in this integration as it can Perform data pre-processing, sorting, storage and retrieval of data, data base querying, graphical display, input and output editing. On the other hand, CA may provide the power for database analysis, temporal dimensionality (for instance by handling multiple iterations), and the flexibility to assign transitional rules and definition of the spatio-temporal neighborhoods.

4.9 Implementation in Rural – Urban Land Conversion

Rural-urban land conversions are by no means randomly distributed. The general characteristics of land use conversions can be revealed through a series of development profiles such as the plotting of the quantity of land use conversion against distance from the city centre. Urban land use models clearly show that land development is constrained by location and geographical conditions. More precisely, urban economics establishes development propensity/probability through regression methods. Logistic regression or the multinomial logic model, for example, can be used to examine the relationship between land use changes and their locational characteristics. However, the regression method is essentially static. While it effects the global distribution of land use conversions in the metropolitan area, the method does not reveal the self-organizing nature of land development, i.e. the clustering of land uses at a local scale or the level of development sites. Urban land development consists of two interrelated processes—that of spontaneous growth and that of self-organized growth. The former represents a process that is independent of sequential land use changes. Land conversions take place according to the demand and supply relationship through development propensity. The chance of land conversion at any place is raised through the clustering of land development in the neighborhood. In a CA simulation, the two processes should be appropriately addressed.

The relationship between development factors and urban spatial structure is conceptualized by the bid-rent theory in urban Economics and Geography. The main determinant of urban land use change, according to the monocentric bid-rent theory, is the
distance to the city centre. Along with the increase in the distance to the city centre, accessibility decreases and transport cost increases. Divergent land users have divergent utility functions, making trade between lands rent and transport cost. The urban land model provides a clue for land development simulation. Rather than simulate land use changes based on heuristically plausible land development propensities, it is possible to derive or calibrate land development probability from the observation of land use changes.

**Implementation in rural-urban land conversion:** The above procedure was applied to simulate rural–urban land conversion in Bangalore Metropolitan City Region. Sequential land use data were used. Through the overlay of land use layers of 2001 and 2009 in ARC GIS, land use changes in this period were identified. The changes were then examined through spatial analysis, in particular the relationship between the distribution of developed sites and their physical and location characteristics. These characteristics are described by a number of ‘contextual’ development attributes.

### 4.10 Selection of Criteria – Local to Global

Derivation of Transition Rules One of the novelties of this model is the design and development of a set of transition rules based on fuzzy set theory rather than probability theory, as applied in previous studies. To replicate realistically the spatial dynamics and processes of urban growth, several transition rules were developed. These were constructed in two stages: (i) by identifying ten spatially-based factors; and (ii) by creating three ‘driving forces’ for urban growth. The driving forces were developed to reflect the main processes shaping the Peri-urban growth of Bangalore Metropolitan City. These drivers were derived from reviews of literature, analysis of local data and expert knowledge. Explanation of the spatial factors and corresponding driving forces and their characteristics such as Roads including Major roads, Ring Roads, Nice road, artillery roads and others. Railways tracks including metro and mono. Lakes, major bus stops and dumping yards.

The selected criteria used for the study area and the selected pockets are different because of the physiographic, demography, social economical factors. The model is comprised of three interlinked software modules: (i) calibration; (ii) simulation; and (iii) prediction. These modules and the framework were designed to be generic, flexible and extensible. Together, the three modules form a prototype Spatial Planning Support System (SPSS). Wu (1998) argued that
there is a limited link between urban CA models and an explicit decision-making process; however, the work here aims to address this gap, at least in part if not fully.

4.11 Particular Criteria’s- Roads, Railways, Lakes, Bus Stops and Dumping Yards

To Create Cellular Automata modeling for Bangalore Metropolitan City some weighted criteria’s have been chosen those are listed below.

<table>
<thead>
<tr>
<th>Sl No</th>
<th>Criteria</th>
<th>Types</th>
<th>Remarks</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Roads</td>
<td>Important Major Roads National and State Highways Core and Ring Roads Nice Roads and Other</td>
<td>2600 KM</td>
</tr>
<tr>
<td>2</td>
<td>Railways and Its Associated Features</td>
<td>Indian Railway Namma Metro (BMRCI) Mon Railways and Commuters Rail</td>
<td>958 KM</td>
</tr>
<tr>
<td>3</td>
<td>Bus Stops</td>
<td>Important Bus Stops Satellite and TTMC Private Bus Stops</td>
<td>43 Bus Stops</td>
</tr>
<tr>
<td>4</td>
<td>Lakes</td>
<td>Dry Lakes Developed Lakes</td>
<td>236 Lakes</td>
</tr>
<tr>
<td>5</td>
<td>Dumping Yards</td>
<td>Working and Non-working</td>
<td>6 Dumping Yards</td>
</tr>
</tbody>
</table>

Creating Cellular Automata Model Using Arc GIS 9.3 Version following are the some of the important steps.
# Open all the Layers, ex. Bus Stops, Railways, Roads, Lakes and Dumping Yards.
# Right Click on the Arc Toolbox.
# Select New Toolbox and Name it as CA.
# Right Click on CA, go to new and click on Model.
# Go to Model Menu and click on Properties to set the environment.
# Check the Cartography Settings and General Settings.
# Click Values on Model Properties Window.
# Select General Settings.
# Select same layer as Roads instead of default in the extent. Click on Ok and apply for the corrections. Select a Layer and drag to Model Window. Open Spatial Analysis Tools in Arc Toolbox, Click on Distance to open Euclidean Distance Tool. Select the Euclidean Distance Tool and Drag to Model Window.

# Click on add connection tool and join the Layer and Euclidean Distance Tool. Click Output Distance and Name the Layer. Run the Model and right click on the Output Distance and click on Add to Display. Follow the Same procedure for all the layers and Prepare Euclidean Distance Maps.

**The Euclidean Distance Functions** describes each cell's relationship to a source or a set of sources. There are three Euclidean functions:

- Euclidean Distance gives the distance from each cell in the raster to the closest source. Example of usage: What is the distance to the closest town?
- Euclidean Allocation identifies the cells that are to be allocated to a source based on closest proximity. Example of usage: What is the closest town?
- Euclidean Direction gives the direction from each cell to the closest source. Example of usage: What is the direction to the closest town?
Map 4.2 Euclidean Distance Map of

A- Dumping Yards
B- Major Bus Stops
C- Major Roads
D- Railways and its Associates
E- Lakes
Reclassifying Raster Data’s: By reclassifying, you can modify the values in an input raster and save the changes to a new output raster. There are many reasons why you may want to do this, including replacing values based on new information, grouping entries, reclassifying values to a common scale (for example, for use in suitability analysis), setting specific values to No Data, or setting No Data cells to a value.

Replacing values based on new information

1. Click the Spatial Analyst dropdown arrow and click Reclassify.
2. Click the Input raster dropdown arrow and click the raster with the values you want to change.
3. Click the Reclass field dropdown arrow and click the field you want to use.
4. Click the New values you want to change and type a new value.
5. Click all other new values (use the Shift key) and click Delete Entries. All other values will remain the same in the output raster.
6. Optionally, click Save to save the remap table.
7. Specify a name for the output, or leave the default to create a temporary dataset in your working directory.
8. Click OK.

Grouping entries

1. Click the Spatial Analyst dropdown arrow and click Reclassify.
2. Click the Input raster dropdown arrow and click the raster with the values you want to group.
3. Click the Reclass field dropdown arrow and click the field you want to use.
4. Click the Old values you want to group (click one, hold the Shift key, and click the next one), then right-click and click Group Entries.
5. Give the grouped entry and other Old values, the new values you want them to have.
6. Optionally, click Save to save the remap table.
7. Specify a name for the output, or leave the default to create a temporary dataset in your working directory.
8. Click OK.
Reclassifying values of a set of rasters to a common scale

1. Click the Spatial Analyst dropdown arrow and click Reclassify.
2. Click the Input raster dropdown arrow and click the raster with the values you want to prioritize.
3. Click the Reclass field dropdown arrow and click the field you want to use.
4. Click the New values input box for each entry and prioritize the entries. This is subjective according to your spatial problem—for example, preference, cost, or time.
5. Optionally, click Save to save the remap table.
6. Specify a name for the output, or leave the default to create a temporary dataset in your working directory.
7. Click OK.

Changing the classification of input ranges

1. Click the Spatial Analyst dropdown arrow and click Reclassify.
2. Click the Input raster dropdown arrow and click the raster with the values you want to reclassify.
3. Click the Reclass field dropdown arrow and click the field you want to use.
4. Click the Classify button.
5. Click the Method dropdown arrow and choose a classification method to reclassify your input data.
6. Click the Classes dropdown arrow and choose the number of classes into which your input data will be split.
7. Click OK.
8. Modify the New values for your output raster if appropriate.
9. Specify a name for the output, or leave the default to create a temporary dataset in your working directory.
10. Click OK on the Reclassify dialog box.
Modeling Peri-Urbanization of Bangalore Metropolitan City – A Geoinformatic Approach

Map 4.3 Reclassified Map of

A-Dumping Yards
B-Major Bus Stops
C-Major Roads
D-Railways and its Associates
E-Lakes
Weighted Overlay: Weighted Overlay is a technique for applying a common measurement scale of values to diverse and dissimilar inputs to create an integrated analysis. Geographic problems often require the analysis of many different factors. For instance, choosing the site for a new housing development means assessing such things as land cost, proximity to existing services, slope, and flood frequency. This information exists in different raster layers with different value scales: dollars, distances, degrees, and so on. You can't add a raster of land cost (dollars) to a raster of distance to utilities (meters) and obtain a meaningful result. Additionally, the factors in your analysis may not be equally important. It may be that the cost of land is more important in choosing a site than the distance to utility lines. How much more important is for you to decide. Within a single raster layer, you must usually prioritize values. For example, a value of 1 represents slopes of 0 to 5 degrees, a value of 2 represents slopes of 5 to 10 degrees, and a value of 3 represents slopes of 10 to 15 degrees. If slope is a criteria in finding a new site, for example, and your evaluation scale is from 1 to 9 by 1, you might give a scale value of 9 to the input value of 1 (the most suitable areas with least steep slopes), a scale value of 6 to the input value of 2 (the second most suitable slopes), and a scale value of 3 to the input value of 3 (the least suitable, steepest slopes). If it was decided that slopes greater than 15 degrees would not be considered, all input values greater than 3 would be assigned a scale value of restricted to exclude them.

Weighted Overlay only accepts integer rasters as input, such as a raster of land use or soil types. Continuous (floating point) rasters must be reclassified as integer before they can be used. Generally, the values of continuous rasters are grouped into ranges, such as for slope, or Euclidean distance outputs. Each range must be assigned a single value before it can be used in the Weighted Overlay tool. The Reclassify tool allows for such rasters to be reclassified. You can either leave the value assigned to each range (but note the range of values to which the new value corresponds) or assign weights to the cell values in the Weighted Overlay dialog box later, or you can assign weights at the time of reclassifying. With the correct evaluation scale chosen, simply add the raster to the Weighted Overlay dialog box. The cells in the raster will already be set according to suitability or preference, risk, or some similarly unifying scale. The output rasters can be weighted by importance and added to produce an output raster.
**Focal Statistics: From Neighborhood Tool:** Neighborhood functions create output values for each cell location based on the value for the location and the values identified in a specified neighborhood. The neighborhood can be of two types: moving or search radius. Moving neighborhoods can either be overlapping or non-overlapping. Overlapping neighborhood functions are also referred to as focal functions and generally calculate a specified statistic within the neighborhood. For example, you may want to find the mean or maximum value in a 3 x 3 neighborhood. The high and low pass filter functions, which smooth and accentuate data, are variations of the overlapping neighborhood statistics function. The non-overlapping neighborhood functions, or block functions, allow for statistics to be calculated in a specified non-overlapping neighborhood. The block functions are particularly useful for changing the resolution of a raster to a coarser cell size. The values assigned to the coarser cells can be based on a separate calculation, such as the maximum value in the coarser cell, as opposed to using the default nearest neighbor interpolation. Search radius functions perform various calculations based on what is in a specified distance from point and linear features. The following is a list of the tools in the Neighborhood toolset followed by a brief description of each. The neighborhood tools are generally divided into two types of neighborhoods: moving or search radius. Moving windows can be either overlapping (Focal Statistics, Filter, and Focal Flow) or non-overlapping (Block Statistics). Search radius neighborhood tools are built around a type of feature (Line Statistics and Point Statistics).

Spatial Analysis Tools → overlay → Select Weighted Overlay and drag to Model Builder Window. Double click on the output layer and save by required name, Double Click on weighted overlay and enter the survey data’s in the place of % influence in the weighted overlay table. Run the model to get the result.

Navigation to open the neighborhood Tool. Spatial Analysis Tools→ Neighborhood Tool → Focal Statistics. Select Focal Statistics and drag to the model create window. Connect with the weighted final Output. Name the focal statistics. Double click on focal statistics tool and set the statistical type. Click on ok and apply. Run the model to execute the programme. Right click on the tool and add to displays.
Table 4.2: Survey Data’s from the Different corner of the study area
(Data Collected through the Survey for CA Model Creation met the local persons and ask the question regarding the selected criteria)

<table>
<thead>
<tr>
<th>Sl No</th>
<th>Criteria</th>
<th>BMC</th>
<th>Whitefield</th>
<th>Peenya</th>
<th>Kengeri</th>
<th>BIAL Road</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Roads</td>
<td>27</td>
<td>10</td>
<td>10</td>
<td>07</td>
<td>10</td>
<td>64</td>
</tr>
<tr>
<td>2</td>
<td>Railways and Its Associated Features</td>
<td>22</td>
<td>04</td>
<td>06</td>
<td>07</td>
<td>05</td>
<td>44</td>
</tr>
<tr>
<td>3</td>
<td>Bus Stops</td>
<td>28</td>
<td>06</td>
<td>05</td>
<td>06</td>
<td>07</td>
<td>52</td>
</tr>
<tr>
<td>4</td>
<td>Lakes</td>
<td>22</td>
<td>05</td>
<td>03</td>
<td>05</td>
<td>03</td>
<td>38</td>
</tr>
<tr>
<td>5</td>
<td>Dumping Yards</td>
<td>01</td>
<td>00</td>
<td>01</td>
<td>00</td>
<td>00</td>
<td>02</td>
</tr>
<tr>
<td></td>
<td><strong>Total</strong></td>
<td>100</td>
<td>25</td>
<td>25</td>
<td>25</td>
<td>25</td>
<td>200</td>
</tr>
</tbody>
</table>

Flow Chart 4.1: Creating Cellular Automata Model using GIS Software
Map 4.4: Weighted Overlay Map show the Expected Area of Urban Growth

Map 4.5: CA for Bangalore Metropolitan City
Further this Cellular Automata Model can be used for the Projection of the result. To Predict the Result, add the Current Result with the actual year imagery and you will get the future predictions. To get the future prediction we have to add Focal Statistics Weightage Result with the 2009 Satellite Imagery, Note: that satellite imagery should have only two classes, 1 represent Urban and 0 represent Non-Urban. Tools are available in Spatial analysis Tools → Math → Plus. Select Plus tool set and drag into model create window. Add 2009 Satellite Imagery as layer, and drag to model create window. Connect 2009 recoded Satellite image and Focal Statistics Weightage Result (FST) or CA Model to plus tool in math tool and run the model and that is the result of Future 1.

4.12 Peri-urban Regions of Bangalore Metropolitan City

After creating the Cellular Automata Model for Bangalore Metropolitan City the demarcation of the Peri-urban region has become very easy, but this cellular automata model is based on the Roads, Railways, Bus stops, Lakes and Dumping Yards. It also proved that Peri-urban region in Bangalore Metropolitan City starts after the boundary of the BBMP Region. The map shown below depicts the area which comes under the Peri-urban region.
On the basis of the above map the study area is divided into Urban, Rural and Peri-urban region. This is near to the actual fact and figure what we can see in the Bangalore metropolitan City. The major areas coming under the Urban class are Basavanagudi, Wilson Garden, Shanthi Nagar, Majestic, M G Road, Market, Guttahalli, Hanumanthanagara, N R Colony, Thyagaraja Colony, Gandhi Nagar, Sheshadri Puram, Cubbonpet, Kumarapark Etn, Vasantha Nagar, Jayanagara, K H Road, Malleshwaram, Magadi Road, Chamaraipet, Mavli, Kalasipalya, Banashankari, KHB Colony, Prakashnagar, Mahalakshmi Puram, Matthikere, Austin Town, Ashok Nagar, Indiranagar, Tasker Nagar, Domalur, Lingaraja Puram, CMH Road, Vijayanagara, Attiguppe, Nagavara, Heenuru, Ramapura, Kannamangala, Whitefield, Sarjapura, Kengeri, Malathahalli, Jakkur, Nagarabhavi, Kumbalagudu, Uttahalli, Vasanthapura, Sarakki, Hulimavu, Gottigere, Banasawadi, Horamavu, K R Puram, R M Nagara, Jalalhalli, Abbigere, Yeshavanthapura, Laggere, Varthur, Beguru, Tippasandara, Hudi, Narayanapura, Maahadevapura and Bettadahalasuru.

The major Peri-urban areas are Dasanapura, Nagaruru, Gajagadhahalli, Lakshmipura, Betahalli, Kammasandra, Kadabagere, Machohalli, Kumbaranahalli, Mllasandra, Valepura, Kotur, Harohalli, Jantagondanahalli, Domasandra, Kenchanpura, Kannenahalli, Devagere, Gundur,
Marasandra, Mandur, Aduru, Kuduregere, Huskuru, Hesaraghatta, Gangavara, Bagaluru, Doodajala and Budhigere.

The Peri-urban regions are the Transition zone between the Urban and Rural. It is influenced by the urban as well as rural. Above mentioned Peri-urban regions are mainly influenced by the urban phenomena. In the last Decade Bangalore Metropolitan City have tremendous growth and it leads to positive impact on Peri-urbanization.

4.13 Selected Pockets of Peri-urban Regions for the study

For the further research some of the selected pockets have been selected, those are having different functionalities. Those pockets are

1. Peenya (Industrial Development)
2. Whitefield (Information Technological Development)
3. Kengeri (Residential Development)
4. BIAL Road (Multi-functional Development)

Map 4.8: Selected Pockets of Peri-urban Regions