CHAPTER 2

LITERATURE REVIEW

2.1 GENERAL

The strength of any research is drawn from the background literature which gives insight of the subject matter, i.e., the research problem, the tools and techniques available, the applicability of such tools and techniques for specific cases, how the specific case study differs from the cases dealt in the literatures and so on. The study of literature gives the understanding on the data requirement and the limitations of the research and helps in deciding the methodology of the research. Therefore, the literature related to the thesis topic is reviewed in detail under the following divisions:

I. Urban Growth Dynamics and Urban Planning
II. Factors influencing Urban Growth
III. Urban Modeling and Simulation
IV. Cellular Automata
V. Scenario Planning
VI. Land allocation for future

2.2 URBAN GROWTH DYNAMICS AND URBAN PLANNING

Urban growth is the spatial pattern of land development and the process of attaining a form influenced by various factors. Urban development
is conceived broadly and simply as change in the city – whether it be the expansion of population and land area, shifts in land-use patterns or transportation systems of the city, changes in the pattern of industrial or commercial development, or alterations in the community’s social, political, and economic institutions (Chapin & Weiss 1962). Urban land use expansion is driven by population growth, social and economic development (Liu & Prieler 2002).

Allen (1996) defines urban growth as a system resulting from complex interactions between urban social and economic activities, physical ecological units in regional areas, and future urban development plans. This interaction is an open, nonlinear, dynamic, and local process, which leads to the emergence of global growth patterns. The urban growth process is a self-organised system (Cheng & Masser 2004). The term ‘process’ generally refers to a sequence of changes in space and time - spatial processes and temporal processes, respectively. It should be noted that, strictly speaking, spatial and temporal processes cannot be separated precisely, as any geographical phenomenon is bound to have both a spatial and a temporal dimension. An understanding of change through both time and space should, theoretically, lead to an improved understanding of change and of the processes driving change. However, a spatial process is much more than a sequence of changes. It implies a logical sequence of changes being carried out in some definite manner that lead to a recognizable result.

Urban land use dynamics are the direct consequence of the action of individuals, public and private corporations acting simultaneously in time over the urban space. As a consequence, cities are the spatial result in time of all these influences, which continuously contribute to shape the city (Barredo et al 2003). Urban land use represents an intense and complete transformation of the natural environment for its essential construction of urban fabrics.
including residential, industrial and infrastructure development. Urban land use expansion is driven by population growth, social and economic development (Liu & Prieler 2002).

Bhatta et al (2010) defines urban development as the process of emergence of the world dominated by cities and by urban values. The authors quote the idea of Clarke (1982) that it is important to draw a clear distinction between the two main processes of urban development viz., urban growth and urbanization. Urban growth is a spatial and demographic process and refers to the increased importance of towns and cities as a concentration of population within a particular economy and society. It occurs when the population distribution changes from being largely hamlet and village based to being predominantly town and city dwelling. Urbanization, on the other hand, is aspatial and social process which refers to the changes of behaviour and social relationships that occur in social dimensions as a result of people living in towns and cities. Essentially, it refers to the complex change of life styles which follow from the impact of cities on society.

They state that the urban growth should be analyzed both as a pattern of urban land-use i.e., a spatial configuration of a metropolitan area in a temporal instant and as a process, namely as the change in the spatial structure of cities over time. Urban growth as a pattern or a process is to be distinguished from the causes that bring such a pattern about, or from the consequences of such patterns. If the urban growth is considered as a pattern it is a static phenomenon and as a process it is a dynamic phenomenon. Analysis of urban growth, as a pattern or process, is an essentially performed operation by the city planners and administrators, proponents, and other stakeholders. However, stakeholders are generally interested in the future pattern of urban land-cover rather than the past or present in view of their investment goals; but the city administrators/planners and proponents require
analyzing the pattern of urban growth for the past and present in order to prepare for the future.

Bringing the development of the urban area into harmony with its environment and the overall system of settlements is one of the basic tasks to be undertaken in order to achieve the general goal of sustainable human settlements in an urbanizing world. Geographically-balanced structures form part of this goal, achieved through monitoring the growth of urban populations. Population growth in urban areas needs to be monitored and harmonized so that it does not create unmanageable densities and population concentrations. High population growth without accompanying infrastructure development, adequate supply of basic services, accessible and affordable land and shelter, sufficient employment and economic opportunities is conducive to urban disorders and environmental degradation (United Nations Human Settlements Programme 2004).

Batty et al (2004) describes Urban Planning as a function of government which was first institutionalized over one hundred years ago. It is focused on making cities more attractive, efficient and equitable place in which to live but its history has been far from successful as it fails to anticipate change which originates from the bottom up. The failure of urban planning is as much a consequence of our inability to understand how cities work as it is of any political or ideological reaction against the idea of control and government. Process rather than product, function rather than form, time rather than space are all important for a better understanding. They have explored cities through three related perspectives on change: continuity which contrasts with discontinuity and bifurcation, transformation where forms and functions evolve from one pattern to another, and emergence which concerns the way qualitatively new and novel structures arise. These dynamics imply processes operating at different temporal rates and spatial scales.
At very fine spatial scales, growth involves individual transitions which are measured with respect to land use, occupancy and density, and change can be slow or fast, gradual or abrupt. But as we scale up, then this volatility is averaged out and at the level of the whole town or metropolis, the change in spatial pattern appears slow and gradual, notwithstanding the fact that growth of absolute volumes of activity may be proceeding exponentially. Cities evolve to a self-organised level and persist at this level until some radical change in technology pushes such systems into another regime. The abruptness of change in cities depends very largely on the scale at which we observe it and the time interval over which it occurs.

The urban processes from local sprawl to global urbanization, affect both natural and human systems at all spatial scales (Dietzel et al 2005). Their study has confirmed that the urban growth can be characterized as having two distinct processes, diffusion and coalescence, with each process following a harmonic pattern. The authors describe that in general, the patterns of urbanization are a consequence of socioeconomic, natural and technological factors that drive and influence the evolving spatial structure of cities. The process starts with the expansion of an urban seed or core area. As the seed grows, it disperses growth to new development centres or cores. While urban diffusion continues, it is accompanied by organic growth which leads to the outward expansion of existing urban areas and the infilling of gaps within them.

It is important at this juncture to understand that ‘land cover’ differs from ‘land-use’ (Bhatta 2010). ‘Land-cover’ corresponds to the physical condition of the ground surface, for example, forest, grassland, cropland, and water; while ‘land-use’ reflects human activities such as the use of the land, for example, industrial, residential, recreational, and agricultural. Land-cover refers to features of land surface, which may be natural, semi-
natural, managed, or manmade. They are directly observable by a remote sensor. Whereas, land-use refers to activities on land, or classification of land according to how it is being used. Land use is the one referred to throughout this thesis.

Land use and land cover pattern of a region is an outcome of natural and socio-economic factors and their utilization by man in time and space (Saxena & Agrawal 2008). Land use change in metropolitan areas typically reflects economic development and population growth. Thus the analysis of spatial-temporal patterns for land use/cover provides an objective basis for understanding the relationships between urban growth and related economic, population and environmental factors. Change detection for land use/cover categories, through the integration of satellite imagery, environmental and socio-economic data, has been commonly used for the analysis of the dynamic pattern of urban growth (Liu & Zhou 2005). Urban planning usually involves the comparison between a set of planning scenarios and development options before making a plan. The analysis of alternative planning options is an essential part of plan making (Li & Yeh 2002a).

At local scale, the process of urban dynamics can be understood in three main phases as explained by Barredo et al (2003). In real situations, the three phases probably work simultaneously as detailed below, producing what is known as a complex system.

**Phase I:** From the set of the available land in a city represented by the bigger cube in Fig. 2.1, a set of factors behaving in a linear deterministic way produce a subset of areas which show simultaneously the best accessibility, the best suitability and the right land use zoning status are prone to be occupied by some land use. In this phase, the factors are not very dynamic and remain stable for some time period until some external action modifies it (For example, the creation of a new motorway will modify the accessibility
parameter) and so the process of urban dynamics in this phase can be modelled using a linear deterministic and more or less static function.

**Phase II:** In the second phase, another group of urban land use factors at local scale come into play using the subset of areas generated in the first phase as input. These factors initiate a non-linear dynamic process in which the current land use pattern and the local-level interactions between land uses combine to create the distribution of new built-up areas and changes from one urban land use to another.

**Phase III:** The third phase gives the system its stochastic character exhibited by cities. Because of the stochastic nature of the system some places that have been highly ranked in the first phase and established to be likely occupied by some land use in the second phase may be discarded or can be occupied by a less proper land use due to human-related decisions.

Figure 2.1 Three dimensional representation of the factors which actuate in urban land use dynamics in Phase I
Urban development is a complicated dynamic process, which involves various physical, social and economic factors. The complexity lies in the unknown amount of factors, multi-scale interactions among factors and its unpredictable dynamics (Jianquan & Masser 2001). Lichfield (1956) states that land utilisation takes place within the three main frameworks of physical, institutional and economic factors.

Metropolitan growth is shaped in large part by at least three different sets of public policy tools viz., infrastructure investment policy (including sewer, water, and transportation); open space protection programs & public land ownership; and local land use planning policies (Mondale & Fulton 2003). The location and size of infrastructure investments creates a "pull" factor, attracting urban growth to areas where capacity exists. Publicly owned land and protected open space exercise a "push" factor, deflecting growth from locations where it might otherwise be viewed as desirable by the market. And local land-use planning policies organize urban growth patterns around those push and pull patterns through decisions about density and scale of development in areas where growth is likely to occur given these other factors.

Barredo et al (2003) recalls Waldo Tobler’s (1970) First law of Geography, “Everything is related to everything else, but near things are more related than distant things” which helps in understanding urban dynamics. According to this law, the neighbourhood space of a feature, even beyond the adjacent space, can influence the feature as a function of distance. However, in addition to Tobler’s law, more factors would have to be taken into account to understand urban dynamics. Barredo et al have shown that urban activities
in the science of spatial planning can be identified under the following five groups of factors:

(i) Environmental characteristics: relates to constraints of urban growth such as natural barriers.

(ii) Local-scale neighbourhood characteristics: relates to the present and past land use patterns and their dynamics. Land use patterns usually represent the strongest influence for the dynamics of land use. Distance from new features to existing land uses and the type of these land uses drive the urban dynamics at local scale.

(iii) Spatial characteristics of the cities (i.e. accessibility): relates to the spatial characteristics such as distance to the centre, accessibility, flows or transport networks. For example, new links in the road network might contribute enormously to urban dynamics as an attractor for urban land uses.

(iv) Urban and regional planning policies: relates to land use zoning status. Through land use zoning plans the city is regulated to be occupied by land uses in space and time.

(v) Factors related to individual preferences, level of economic development, socio-economic and political systems: These are the most complicated to understand and model. This group of factors is also related to human decision-making processes, which in most cases are qualitative, evolve in time and can be intransitive and therefore difficult or almost impossible to predict.
Many studies have identified various sets of factors (variables) influencing urban growth in different urban areas under different conditions. Chapin & Weiss (1962) had identified the following variables for studying the dynamics of urban growth:

(i) Location of major highways
(ii) Location of work areas
(iii) Location of city’s water service area
(iv) Location of city’s sewer service area
(v) Location of city’s fire protection service area
(vi) Location of city’s police station service area
(vii) Location of city’s school service area
(viii) Location of city’s zoning jurisdiction
(ix) Location of city’s sub-division control jurisdiction
(x) Location of areas of mixed land use
(xi) Location of blighted residential areas.

In one of the premiere works in the field of urban dynamics, Steinitz & Rogers (1970) had used the following variables for a residential allocation model for South west Sector of the Boston Region.

(i) Land value (independent variable)
(ii) Tax rate
(iii) Access to a limited access highway
(iv) Access to route 128
(v) Access to Province
(vi) Access to Framingham
(vii) Distance from an elementary school
(viii) Estimation of visual quality
(ix) Educational dollar expenditure per pupil.

A decision support system was developed for promotion of residential apartments in Chennai city, by Raghavendran (2001) using the following variables, which are very much relevant to the present study which focuses on Chennai Metropolitan (sub urban) Area:

(i) Proximity to city centre
(ii) Land cost
(iii) Availability of ground water
(iv) Availability of metro water (supply of water by the municipal local bodies for individual pipe lines / street pipes)
(v) Availability of sewerage system on the abutting road
(vi) Site to be free from inundation
(vii) Proximity to educational institutions
(viii) Proximity to railway station
(ix) Proximity to bus terminal
(x) Proximity to hospital.

Yeh & Li (2002) had developed a cellular automata model using neural networks to simulate potential or alternative urban development patterns based on different planning objectives for the city of Dongguan, China. In this study, the following seven spatial variables are defined to
represent the site attributes of each cell for the simulation of urban development:

(i) Distance to the major (city proper) urban areas
(ii) Distance to suburban (town) areas
(iii) Distance to the nearest road
(iv) Distance to the nearest expressway
(v) Distance to the nearest railways
(vi) Neighbourhood development level
(vii) Agricultural suitability.

The variables used by Almeida et al (2003) for determining urban land use change through simulation are as follows:

(i) Area served by water supply
(ii) Medium – high density of occupation (25% to 40%)
(iii) Existence of social housing
(iv) Distances to ranges of commercial concentration
(v) Distances to industrial zones
(vi) Distances to residential zones
(vii) Distances to peripheral residential settlements
(viii) Distances to isolated institutional use
(ix) Distances to main existent roads
(x) Distances to the service and industrial axes
(xi) Distances to planned roads
(xii) Distances to peripheral roads.
The following 20 variables including 12 variables representing biophysical, spatial policy, other socio economic factors, and 8 measures of accessibility, had been used by Conway (2005) to represent correlates of urban development location in the coastal zone of New Jersey:

(i) Meters to nearest highway exit following the local road network
(ii) Meters to nearest road
(iii) Percentage of urban land within 1 km neighborhood
(iv) Meters to nearest urban cell in (the year) 1986
(v) Meters to nearest protected open space in 1986
(vi) Meters to nearest body of water in 1986
(vii) Percentage of protected open space within 1 km neighborhood in 1986
(viii) Percentage of open water within a 1 km neighborhood in 1986
(ix) 1986 state of cell is barren
(x) 1986 state of cell is forest
(xi) 1986 state of cell is wetlands
(xii) 1986 state of cell is agriculture
(xiii) Cell is located within 100-year floodplain
(xiv) Cell is located within Pinelands Management Areas
(xv) Minimum lot size allowed by municipal zoning regulations
(xvi) 1986 population density of municipality
(xvii) Presence of sewer service
(xviii) Percentage of urban land within 0.1 km neighborhood in 1986

(xix) Percentage of protected open space within 0.1 km neighborhood in 1986

(xx) Percentage of open water within 0.1 km neighborhood in 1986.

Significant explanatory variables were identified by using a step-wise selection process. As there was some correlation between the independent variables, most notably the features defined by Euclidean distance, a 1 km neighborhood, and a 0.1 km neighborhood, alternative combinations of variables were included in different analyses. Only six out of twenty explanatory variables (variables i, ii, iii, vii, ix and x) were best able to account for the location of new urban development between 1986 and 1995.

Luo & Wei (2009) had used the following variables in a land use conversion model for Nanjing, China. All the variables relate to proximity and neighbourhood characteristics:

(i) Distance to inter-city highway
(ii) Distance to local artery roads
(iii) Distance to railways
(iv) Distance to Yangtze river
(v) Distance to Yangtze river bridge
(vi) Distance to major city centres
(vii) Distance to suburban centres
(viii) Distance to industrial centres
(ix) Density of agriculture land
(x) Density of built up land

(xi) Density of water body

(xii) Density of forest land.

Maithani (2009) had identified that urban growth (in the study area of Saharanpur city, Uttar Pradesh State, India) is defined as a function of the following three factors, also called as causative factors:

(i) Accessibility to roads (connectivity is a major factor affecting the urban growth process)

(ii) Accessibility to the city core, (most of the higher level facilities are located in the city core).

(iii) Accessibility to infrastructural facilities.

Al-Ahmadi et al (2009) in their Fuzzy Cellular Automata Urban Growth Model (FCAUGM) for the city of Riyadh, Saudi Arabia had used the following variables under four factors representing the driving forces:

(i) Topographical constraints factor (physical characteristics):
   - Slope gradient
   - Altitude

(ii) Transport support factor:
   - Accessibility to local road
   - Accessibility to main road
   - Accessibility to major road

(iii) Urban agglomeration and attractiveness factor:
   - Urban density
• Accessibility to town centre
• Accessibility to employment
• Accessibility to socio-economic centres

(iv) Planning policies and regulations factor:
• Planned areas
• Excluded areas

The synthesis of the variables listed above is given in Appendix 1.

2.4 URBAN MODELING AND SIMULATION

The field of urban modeling is concerned with designing, building and operating mathematical models of urban phenomena, typically cities and regions. It helps planners, politicians and the community to predict, prescribe and invent the urban future (Batty 1976). Urban dynamics are often simulated with rule-based Urban Growth Models (UGMs), e.g., Cellular Automata (CA) and Agent Based Models (ABMs) (Tayyebi et al 2011).

Batty & Torrens (2001) define that models are a simplification of some reality which involves distilling the essence of that reality to some lesser representation. He highlights that simulation differs from modeling in that simulations are dynamic and open-ended. Urban system is complex. He quotes the definition given for complex systems given by Holland (1995), who describes complex (adaptive) systems as being systems that maintain their structure and coherence under all imaginable changes, in short through adaptation. Also he quotes Allen (2001) who says, “The simplest definition of a complex system is one that can respond in more than one way to its environment. The ‘choice’ in response arises from the fact that non-linear
processes within the system can potentially amplify microscopic heterogeneity hidden within it”.

Batty & Torrens (2001) explain the difference between traditional models and the new generation models which relate to how causal structures are treated. He argues that, in traditional urban models, the focus is on simple causes. In so far as these are complicated in any way, it is through making the system extensive, through repeating these simple causes over many categories but not by elaborating the causal chains that link inputs to outputs. The most extreme variants of this style simply assume that the causal structure is a homogeneous nexus of additive factors as in multiple regressions or in neural nets. The emphasis is largely on validating these kinds of models using data which drives these simple causes. In contrast, complex systems models have multiple causes which display heterogeneity of processes that are impossible to observe in their entirety. The focus is on more qualitative evaluation of a model’s plausibility in ways that relate to prior analysis of the model’s structure. In both styles of model, the wider context is important in validating the model too. What the model is to be used for - its purpose - is all important, particularly so where a degree of belief in its predictions may be suspended because of its complexity. Criteria for developing such models are not well-worked out and in urban systems this has become an important challenge.

Batty (2003) finds the clearest model which broke from the traditions of model building and which illustrated distinctly the problems posed by the current generation of models based on complexity was Forrester’s (1969) *Urban Dynamics model*. He says that validation and testing are the two important components of good model building.

Stephenne & Lambin (2001) group the backward or forward projections of land-use change under two main categories of models viz., (i) empirical models based on an extrapolation of the patterns of change
observed over the recent past, with a limited representation of the driving forces of these changes and (ii) dynamic simulation models based on a thorough understanding of the processes of land-use change. They say that empirical models integrate landscape variables and proximate causes of change in a data rich spatial context. However, the empirical models can only provide short range projections of 5 to 10 years due to the dynamic character of land-use change processes. On the other hand, long range projections require a good understanding of the major human causes of land-use changes in different geographical and historical contexts with an understanding of how climate variability affects both land-use and land-cover. Such understanding is gained through a collection of local scale case studies on land-use dynamics, which highlight how people make land-use decisions in a specific situation. A generalised understanding of the drivers of land-use change, which can be linked to regional scale patterns of change, is gained through a comparative analysis of these case studies.

Land use models are grouped based on disciplinary approaches to explain land use (Silveira & Dentinho 2010). They are:

- **Descriptive models** - predict the factors responsible for changes
- **Stochastic models** consist of probabilistic transition models between pre-defined states of the system.
- **Statistical models** - identify factors causing changes in land use through multivariate analyses
- **Simulation models** highlight interactions between all of elements that comprise the environmental system.
- **Economic land use models** assume that land demand is the main determinant of land use.
• **Integrated spatial models** combine the advantages of spatial simulation models with the qualities of spatial economic models.

### 2.4.1 Types of Urban Modelling Methods

Waddell & Ulfarsson ([http://synthicity.com/introduction_to_urban_simulation.pdf](http://synthicity.com/introduction_to_urban_simulation.pdf)[01.03.2010]) explain that three of the urban modelling methods were used in the earliest operational urban models, dating from the 1960’s and 1970’s: spatial interaction, spatial input-output, and linear programming. Micro simulation was developed in the 1960’s, but not applied to urban modelling until the 1980’s. Since the 1980’s, the development of discrete choice modelling and the emergence of cellular automata and multi-agent simulation techniques have created a proliferation of modelling approaches. They describe the following different models:

(i) **Spatial Interaction Models:** Based on the approach of gravity in physics, which indicates that gravitational pull increases in proportion to the mass of two objects in space, and decreases with the square of the distance separating them, spatial interaction approach include some of the earliest efforts to model systematic spatial patterns of urban land use. Applied to urban settlements and travel, the gravity model implies that travel between two zones increases with the amount of activity in the origin and destination zone, and decreases with the square of the travel impedance between them. The basic model has been extended to model trip destination choices, residential location choices, and employment location choices.
(ii) **Spatial Input-Output Model:** The spatial input-output framework extended the input-output model developed to represent the structure of the U.S. economy (Leontief 1966) to address spatial patterns of location of economic activity within regions, and the movement of goods and people between zones. Zones are treated in a sense as economies that engage in production, consumption, import, and export within the zone and with all other zones in the model. These economic exchanges between zones are denominated in monetary units, and driven by demand for exports. Monetary flows are converted to flows of goods and services by type of vehicle, and of commuting and shopping trips by mode. The approach includes explicit real estate and labour markets, as well as travel demand modelling, and is structured to generate a static equilibrium solution to changes in one or more inputs. Zone sizes in operational applications tend to be large relative to zone sizes used in typical urban travel modelling.

(iii) **Linear Programming Models:** Linear programming models of land use are rare. Linear programming optimizes a global objective function, such as consumer surplus or utility, across the entire model system. The approach is therefore more suited to exploration of alternative land use configurations that might optimize transportation flow, than to reflect realistic behavioural responses to changes in the transportation system or in land use policies.
(iv) **Micro simulation Models:** Micro simulation as an approach essentially implies a model that is applied at the level of the individual. Developed in the late 1950’s and early 1960’s, the method was initially applied to study the effects of social and economic policies. Later it was applied to the formulation of urban models such as MASTER (Mackett 1992), DORTMUND (Wegener 1985), and Urban Sim (Waddell 2002). Spatially-explicit urban models have used combinations of discrete choice models and transition rates, to predict changes in the state of individuals or households, such as entering or leaving the labour force, and their choices such as residence location.

(v) **Discrete Choice Models:** Discrete choice modelling techniques are widely used in travel demand modelling, mostly in the analysis of mode choice. These models are generic in the sense that they do not impose overly-restrictive assumptions on the choice process, and have been shown capable of addressing large and complex choice sets effectively. Discrete choice techniques can be readily used in conjunction with other simulation approaches, such as micro simulation.

(vi) **Rule-Based Models:** Several land use models have been developed in recent years using GIS and a rule-based set of procedures to allocate population, employment, and/or land use. Examples include the ‘CUF’ model (California Urban Future) (Landis 1994) and ‘What If?’ (Klosterman 1999). Such rule-based applications may have a useful role in making models more accessible, but there is a risk that
model users would interpret the models as having a more behavioural basis than their rules actually contain. There are also rule-based methods that are emerging from the field of artificial intelligence, using observed data to generate clarification trees of behavioural rules that are used in micro simulation, such as the Albatross activity-based travel model. A comparison of different urban growth / land use change models (Herold et al <http://www.eo.uni_jena.de/NC5hema/pub/herold_menz_Clarke.pdf> [19.01.2010]) is given in Appendix 2.

(vii) **Cellular Automata:** Cellular automata (CA) models have emerged within the broad field of complex systems as a means of representing the emergent properties of simple behavioural rules applied to cells within a grid. The approach has now been widely applied to urban land cover or land use change. To date, applications have been principally for research purposes rather than operational planning or policy, though efforts are underway to make these models useful for planning purposes. The approach is particularly useful for representing the interactions between a location and its immediate environment, but tends to reflect a fairly abstract representation of agents, decisions, and behaviour, since the models focus on simulating the change in state of individual cells. The CA is dealt in detail in section 2.5.

(viii) **Multi-Agent Simulation:** Multi-agent simulation (MAS) models are related to CA in that both draw on complex systems theory, but differs from CA in that its emphasis is
on emergent system behaviour arising from interactions between agents. The MAS approach is gaining substantial research interest across the social sciences, since it opens new avenues to analyse social behaviour from an interactive perspective.

Steinitz & Rogers (1970) developed an experimental studio course termed as ‘man-machine interaction’, a premiere of its kind to develop a better method of exploration and of interdisciplinary teaching which led to greater understanding of the complexities of urban development and developed methods for actual planning and design processes of the study area. They developed four allocation models viz., an industrial model, a residential model, a recreation and open space model and a commercial model.

The principal data sources for the simulation model were aerial photographs interpreted with field checks, United States Geological Survey (USGS) maps, reports of Massachusetts state agencies and departments, and the United States census. The basic spatial unit for data collection and analysis was 1 km x 1 km Universal Transverse Mercator (UTM) grid. All the data were linked to the grid in computer usable form through an indexing system and were organized for graphic display using the GRID program.

The simulation involved the following steps:

i. USGS maps of the study area were put together on a wall, and one kilometer square UTM grid was scored on each map. Roads and town boundaries were also drawn on the maps.

ii. Land use and its various subcategories assigned with color and symbol, were prepared and pinned to the USGS maps in the process of allocation. Aluminium-headed pins were used
for all new allocations. If a conflict for a cell was present, the chips were pinned on the diagonal. Color coded pins were used for the evaluation models: red for political, green for financial, white for visual and blue for pollution models. When an objection was made by one of these models, its pin would be placed on the offending allocation chip. The evaluation pins would be removed as objections were met, either by argument or by reallocation.

iii. New locations were marked with a clear-headed pin and reevaluated. Conflicts among sectors were similarly resolved and the results evaluated. Finally, with no remaining conflicts or objections, the chips were stapled to the wall surface and all pins removed.

iv. Data files were then updated keypunched and the process was repeated again for the next time period or iteration in that simulation.

2.5 CELLULAR AUTOMATA

Sullivan et al (2000) argues that land uses do not ‘mutate’ like cell cultures on a microscopic slide. Rather, human agents – developers, firms, financiers, regulatory authorities, landlords, tenants, home buyers – manoeuvre, collaborate and compete to change the city for their own purposes. The combination of their activities is what causes ‘state transitions’. They say that Cellular Automaton (CA) based models are increasingly used to investigate cities and urban systems. It was the Hungarian-American, Jon von Neumann, who initiated the scientific study of CA.
Itami (1994) approves that Cellular Automata brought a major breakthrough in the field of simulation of land use changes. The major contributions made by John von Neumann and Stanislaw Ulam in the field of CA model of simulation experienced the takeoff with the advent of digital computing systems and Geographical Information System (GIS).

2.5.1 Definition of Cellular Automata

Torrens (2000b) describes that CA were first devised by John von Neumann and Stanislaw Ulam in the 1940s as a framework for investigating the logical underpinning of life. John von Neumann was the originator of game theory, and pioneer in set theory, quantum mechanics, and the specification of electronic computers and Stanislaw Ulam worked on Monte Carlo simulation and the hydrogen bomb (as part of the Manhattan Project with Edward Teller and was influential in set theory and number theory). Rucker (1999) states that, “One can say that the ‘cellular’ comes from Ulam and the ‘automata’ comes from von Neumann”. Von Neumann and Ulam were interested in exploring whether the self-reproducing features of biological automata could be reduced to purely mathematical formulations - whether the forces governing reproduction could be reduced to logical rules.

Torrens (2000b) further states that the idea for CA owes a great deal to Alan Turing’s specification of an UTM in the 1930s. The UTM was a hypothetical automaton, a machine with limited specifications and ranges of action that was capable of computing anything that could be computed: the UTM was capable of universal computation. A system may be regarded as a universal computer if, given a suitable initial program, it is capable of implementing any finite algorithm through its evolution over time, i.e., that it is capable of producing a working copy as complicated as itself, and the means to make further copies. A universal computer need only be reprogrammed, not rebuilt, to perform any calculation that is thrown at it. He
further explains what exactly a cellular automaton is. An automaton essentially comprises a finite state machine (a Turing-like machine) that exists in some form of tessellated cell-space. The term automaton refers to a self-operating machine, but one of a very distinct nature: “An automaton is a machine that processes information, proceeding logically, inexorably performing its next action after applying data received from outside itself in light of instructions programmed within itself.” Levy (1992) explains how CA differs in an important way from Turing Machines: CA are parallel processors rather than serial processors. In parallel processing, more than one particular process is active at any given time. In serial processing, on the other hand, one stage in the process is computed before the next starts; only one stage is active at any given time.

2.5.2 Elements of Cellular Automata

The elements that comprise an elementary cellular automaton (Torrens 2000b) are:

(a) The lattice or the space on which the automaton exists;

(b) The cell in which the automaton resides, which contains its state(s);

(c) The neighbourhood around the automaton;

(d) Transition rules that describe the behaviour of the automaton; and

(e) The temporal space in which the automaton exists.
2.5.2.1 Lattice

The lattice of CA comprises the space in which the CA exists and evolves over time. In an elementary CA, this lattice is one-dimensional (Figure 2.2). However, lattices can be $n$-dimensional. CA designed for geographic purposes are generally defined in two-dimensions (Figure 2.3), while lattices of several dimensions have been defined in other disciplines. In an elementary CA, lattices are defined in a regular fashion often as grid squares or other combinations of regular shapes (hexagons and triangles have also been used). In theory, CA lattices can extend to infinite proportions within any given dimensionality, but for practical purposes some clever tricks are played to define the edges of CA lattices. Most commonly, CA are designed to wrap around on themselves, corresponding to a circular arrangement for one-dimensional CA, and a torus for two dimensional CA.

![Finite state automaton
(state is "full")](#)

Two-cell
neighbourhood

![Finite state automaton
(state is "empty")](#)

Figure 2.2 One dimensional Cellular Automata
Source: Torrens (2000b)
2.5.2.2 Cell-states

CA cell-states characterize the attributes of finite state machines in a CA lattice. In this sense, they constitute a description of the elemental building blocks and attributes that comprise a CA. In a Turing Machine, states are defined in a binary fashion, as consisting of symbols representing zero or one. Von Neumann, in his CA, provided for the existence of 29 cell states.
2.5.2.3 Neighbourhoods

A neighbourhood comprises the localized region of a CA lattice, from which the finite state machine (cell) draws input. This input forms the information collected from a scan of cells within the neighbourhood template (Langton 1992). A neighbourhood consists of a CA cell itself and any number of cells in a given configuration around the cell.

2.5.2.4 Transition rules

Transition rules are the real engines of change in a CA. They specify the behaviour of cells between time-step evolutions, deciding the future conditions of cells based on a set of fixed rules that are evaluated on input from neighbourhood templates. In a strict CA, these rules are applied uniformly across cells in a synchronous fashion. Transition rules are generally formulated as IF, THEN and ELSE statements that rely on input from a neighbourhood template to evaluate their results. In this sense, transition rules replace traditional mathematical functions in models with rule-based procedures (Batty 1997a). Batty (1997a) argues that there are advantages to this methodological approach: rules reflect how real systems operate; also, they enable complicated systems to be reduced to the simple components that drive their dynamics.

Figure 2.2 shows a one-dimensional CA (its lattice extends in only one dimension) at time $t$ and time $(t + 1)$ in its evolution. The lattice consists of 13 finite state machines (cells), distributed continuously in a one-dimensional space. Each cell state can be in one of two states, either “empty” (depicted by the colour white) or “full” (depicted by the colour brown). Each cell is driven by a transition rule table, which governs the state of the cells in each time-step. In the example given in Figure 2.2, the state of the cells is governed by the following transition rules:
Rule part A

\textit{IF} [cell state is “full”]

\textit{THEN} [proceed to the part B of the rule]

\textit{ELSE} [end]

Rule part B

\textit{IF} [the majority of the cells in the neighbourhood are “empty”]

\textit{THEN} [move one cell to the right along the lattice]

There are two time-steps in the life cycle of the CA. In the first time step, each cell draws input from its neighbourhood, upon which a cell’s finite state machine can base its behaviour in the next time step. Part A of the transition rule picks out those cells in the lattice that are “full”. Part B of the rule asks the “full” cells to scan their two-cell neighbourhood, both to the left and to the right. If that scan discovers that neighbouring cells in its right-hand side neighbourhood are “empty”, then the “full” cell is directed to ‘move’ (really, adjacent cells exchange state values) one cell to the right along the lattice in the next time step.

Torrens (2000b) goes explaining that the two-dimensional CA does not differ radically from one-dimensional CA in formulation; their lattice simply extends in an additional dimension. However, in terms of their simulation capacity, two-dimensional CA differs greatly from their one-dimensional counterparts. Extending the one dimensional CA example from Figure 2.2 into a second dimension, to a situation where the number of possible cell states remains the same (two), but the number of lattice sites grows from 13 to 132, or 169. The number of possible configurations the lattice can now take on grows by orders of magnitude still: the number of possible cell states raised to the power of the number of possible lattice sites, 2169, a significantly larger number than the 8192 possible configurations of the one dimensional CA. Such a large range of possible configurations allows
for the generation of very many scenarios, using very simple modelling frameworks. Of course, intuitively, running two-dimensional CA models makes more sense than one dimension in many examples, including urban applications. The two most commonly defined neighbourhood templates for a two-dimensional CA are the Moore neighbourhood and the von Neumann neighbourhood (Figure 2.3), although researchers have tinkered heavily with neighbourhood template sizes and configurations.

2.5.2.5 Time

As with Turing Machines, time in CA is discrete. Time proceeds in iterative steps of whatever length the model designer cares to conjure. The temporal evolution of cells destroys the independence of initial cell states; instead prompting correlation between cell states at separated sites (Wolfram 1994). As a result, CA can generate structured patterns through their evolution.

2.5.3 Fields of application of Cellular Automata

CA models implemented on computers may serve as a framework for modelling complex natural phenomena in a way that is conceptually clearer, more accurate, and more complete than conventional mathematical systems (Itami, 1994). Application of CA has been explored primarily in the physical and natural sciences at a wide range of scales. Maddox (1987) reported on cellular automata models of galaxy formation. At the other end of the scale, Wolfram (1984) demonstrated the use of cellular automata simulations in the formation of snowflakes and turbulent flows in fluid dynamics (Wayner 1988). Vichniac (1984) has shown that cellular automata may be used to simulate a wide range of processes in physics including percolation and nucleation. Yakowitz et al (1989) reported on the development of cellular automata models of disease epidemics in human populations. More recent work has focused on the cellular automata within an
information theory context, statistical properties of cellular automata and the study of lattice gases, turbulence and fluid dynamics (Manneville et al 1989).

Sullivan and Torrens (2000) list out the wide and sophisticated usage of Cellular Automata (CA) models ranging from study of land use dynamics, regional scale urbanization and polycentricism, urban socio-spatial segregation, development, location analysis, urbanism, urban growth and sprawl.

Batty (1997a) explains the applications of CA models to cities data from the first time computers were used to model urban land use. CA are models in which contiguous or adjacent cells, such as those of that might comprise a rectangular grid, change their states – their attributes or characteristics through the repetitive application of simple rules. The rules for transition from one cell state to another can be interpreted as the generators of growth or vice versa. This change is a function of what is going on in the neighborhood of the cell, the neighborhood usually being defined as immediately adjacent cells, or cells that “in some sense” are nearby. The principle can be stated in its most generalized form as

**IF** something happens in the neighborhood of a cell  
**THEN** some-other-thing happens to the cell.

Many IF-THEN rules might be concatenated; the size and configuration of neighborhoods can be varied from the most local to the entire system; different types of state or development, such as different types of state or development, such as different land uses and their attributes, might be characterized; and different configurations or starting points for these automata can be defined.
The above rule will result in a pattern containing randomly located vacant sites. Therefore the rule is modified so as to generate an entirely compact urban form in the following way:

**IF**

there is at least one developed cell in the Moore neighborhood around the cell in question

**THEN**

the cell is developed with a probability $\rho$.

CA models can be implemented within many types of software. It is possible to program them in spreadsheets such as Excel using the chart function as a means of displaying the 2-dimensional grid, and this is aided even further if the modules for plotting maps within the spreadsheet are available. CA models can be easily developed that use the extensive graphics capabilities of GIS and computer aided design systems packages.

In Geographic Cellular Automata, spatial scale is defined by three components (Menard & Marceau 2005):

(i) the spatial extent – refers to the dimension of the area that is modeled;

(ii) the cell size - specifies the landscape area each cell is going to cover; and

(iii) the neighborhood configuration which determines the distribution and number of neighbors that will have an impact on the evolution of each cell.

Table 2.1 presents the cell size and neighborhood configuration used in geographical applications of CA in some of the studies. Couclelis (1997) acclaims that CA are commonly regarded as having a “natural affinity” with raster data. Torrens (2000b) explains that they seem well suited
to Geographical Information System (GIS) and remotely sensed information. There are other similarities between CA and GIS. Both CA and GIS organize space into discrete areal units (grids in CA, and polygons or grids in GIS). Also, CA and GIS represent attribute information in a layered fashion (themes in GIS and state-spaces in CA), and manipulate that information with operators (overlay techniques, for example, in GIS and transition rules in CA) (Wagner 1997).

### Table 2.1 Geographical applications of CA in some studies

<table>
<thead>
<tr>
<th>Author</th>
<th>Year</th>
<th>Cell size</th>
<th>Neighborhood shape</th>
<th>No. of neighborhoods</th>
<th>Region</th>
</tr>
</thead>
<tbody>
<tr>
<td>Arai and Akiama</td>
<td>2003</td>
<td>92m x 113m</td>
<td>Rectangular (5x5)</td>
<td>24</td>
<td>Periurban region of Tokyo, Japan</td>
</tr>
<tr>
<td>Barredo et al</td>
<td>2003</td>
<td>100 m</td>
<td>Circular (8 cells radius)</td>
<td>172</td>
<td>Dublin (Ireland)</td>
</tr>
<tr>
<td>Batty and Xie</td>
<td>1994</td>
<td>220 m</td>
<td>Moore</td>
<td>8</td>
<td>Savannah region, Georgia (USA)</td>
</tr>
<tr>
<td>Clarke and Gaydos</td>
<td>1998</td>
<td>210 m</td>
<td>Moore</td>
<td>8</td>
<td>Baltimore – Washington region</td>
</tr>
<tr>
<td>Clarke et al</td>
<td>1997</td>
<td>300 m</td>
<td>Moore</td>
<td>8</td>
<td>San Francisco Bay, California (USA)</td>
</tr>
<tr>
<td>Deadman et al</td>
<td>1993</td>
<td>100 m</td>
<td>Moore or Von Neumann</td>
<td>4 or 8</td>
<td>Wellington County, Ontario (Canada)</td>
</tr>
<tr>
<td>Almeida et al</td>
<td>2003</td>
<td>100 m</td>
<td>Moore</td>
<td>8</td>
<td>Bauru region (Brazil)</td>
</tr>
<tr>
<td>Jenerette and Wu</td>
<td>2001</td>
<td>250 m</td>
<td>Moore</td>
<td>8</td>
<td>Phoenix, Arizona (USA)</td>
</tr>
<tr>
<td>Li and Yeh</td>
<td>2000</td>
<td>50 m</td>
<td>Circular (2 cells radius)</td>
<td>20</td>
<td>Region in the south of China</td>
</tr>
<tr>
<td>Theobald and Hobbs</td>
<td>1998</td>
<td>804 m</td>
<td>variable</td>
<td>4 / 8 / 20</td>
<td>Summit County, Colorado (USA)</td>
</tr>
</tbody>
</table>
Table 2.1 (Continued)

<table>
<thead>
<tr>
<th>Author</th>
<th>Year</th>
<th>Cell size</th>
<th>Neighborhood shape</th>
<th>No. of neighborhoods</th>
<th>Region</th>
</tr>
</thead>
<tbody>
<tr>
<td>Vandergue et al</td>
<td>2000</td>
<td>Census sectors</td>
<td>First-order connectivity</td>
<td>-</td>
<td>Bogota (Peru)</td>
</tr>
<tr>
<td>White and Engelen</td>
<td>1993</td>
<td>500 m</td>
<td>Circular (6 cells radius)</td>
<td>112</td>
<td>Atlanta, Cincinnati, Milwaukee, and Houston (USA)</td>
</tr>
<tr>
<td>White and Engelen</td>
<td>1994</td>
<td>250 m</td>
<td>Circular (6 cells radius)</td>
<td>112</td>
<td>Caribbean Island</td>
</tr>
<tr>
<td>White and Engelen</td>
<td>2000</td>
<td>500 m</td>
<td>Circular (8 cells radius)</td>
<td>196</td>
<td>Netherlands</td>
</tr>
<tr>
<td>White et al</td>
<td>1997</td>
<td>250 m</td>
<td>Circular (6 cells radius)</td>
<td>112</td>
<td>Cincinnati, Ohio (USA)</td>
</tr>
<tr>
<td>White et al</td>
<td>2000</td>
<td>250 m</td>
<td>Circular (8 cells radius)</td>
<td>196</td>
<td>St Lucia Island</td>
</tr>
<tr>
<td>Wu</td>
<td>1998</td>
<td>28.5 m</td>
<td>Square (5x5)</td>
<td>24</td>
<td>Guangzhou (China)</td>
</tr>
</tbody>
</table>

Source: Menard & Marceau (2005)

In many cases, state data can be arranged in a GIS or via remotely sensed images before being introduced to the CA. White and colleagues’ model (White & Engelen 1997) represent a plethora of information about cities, such as soil types, precipitation levels, legal restrictions on land use, arranged in many cases as weighted sums. In such cases GIS are ideal for preprocessing CA state-spaces. Other authors have suggested a closer coupling of CA and GIS, suggesting that CA act as the ‘analytical engine’ for a GIS (Wagner 1997). In the Wu and Webster models (Wu & Webster 1998), for example, the CA is called from within a GIS. Yeh (1998) and Yeh & Li (2002) have also developed CA-GIS models for urban research.
2.5.4 Issues in constructing Cellular Automata Models

Sullivan & Torrens (2000) highlight some of the modeling issues involved in constructing CA models which include:

- It can be difficult to reduce all of the activity in an urban cell to a single discrete description, more particularly in case of relatively coarse grids (at say 100m or more resolution).

- It is also difficult to represent some very significant features of the urban environment – transport networks and rivers being the foremost examples, in a grid based cellular world.

- In a formal CA, every state change must be local, and there is no allowance for action-at-a-distance. In a strict CA it is implied that the dynamics take care of distance effects simply because growth and decline appear as spatial diffusion.

- Few urban CA models retain a spatially stationary lattice. But in practice fixed cell states cannot represent the irregular and asymmetrical spatial features such as water bodies and undeveloped land.

- Truly asynchronous cell update in urban CA is unusual.

They have explored some of the possibilities of developing some well-defined, specific departures from the CA formalism, which include:

- Strict formal CA with a small family of geographical process rules

- Cellular models with irregular lattice structures

- Agents in cellular models

- Asynchronous cell update
2.5.5 Application of Cellular Automata

A project-based cellular automaton modeling was developed by Cheng & Masser (2004) for interpreting the spatial and temporal logic between various projects that form the whole of urban growth. An innovative methodology for understanding spatial processes and their temporal dynamics were presented on two interrelated scales—the municipality and project scale—by means of a multistage framework and a dynamic weighting concept. The multistage framework is aimed at modeling local spatial processes and global temporal dynamics by the incorporation of explicit decision making processes. It is divided into four stages: project planning, site selection, local growth, and temporal control. These four stages represent the interactions between top-down and bottom-up decision making involved in land development in large-scale projects. Use of dynamic weighting is an attempt to model local temporal dynamics at the project level as an extension of the local growth stage. As nonlinear function of temporal land development, dynamic weighting can link spatial processes and temporal patterns. The methodology is tested with reference to the urban growth of a fast growing city—Wuhan, in the People's Republic of China from 1993 to 2000. The findings from this research suggest that this methodology can be used to interpret and visualize the dynamic process of urban growth temporally, transparently, globally and locally.

The SLEUTH urban growth model was used by Dietzel et al (2005) to project urban growth into the future for three fast growing economic urban regions of California’s Central Valley. SLEUTH is a model that is exhaustively calibrated based on the historical patterns and dynamics of an urban system. Calibration of SLEUTH produces a set of five parameters (coefficients) that describe an individual growth characteristic that, when combined with other characteristics, can describe several different growth
processes. The five coefficients (Slope, Land use, Exclusion, Urban Extent and Transportation) control the behavior of the system and are predetermined by the user at the onset of every model run. These parameter values drive the four transition rules, which simulate (1) spontaneous (of suitable slope and distance from existing centres), (2) diffusive (new growth centres), (3) organic (infill and edge growth) and (4) road-influenced growth (a function of road gravity and density). A constant resolution of 100m x 100m grid cell size was adopted in the model. The eight metrics used in the model are percentage of the landscape covered by urban land, the urban patch, the edge density, the mean Euclidean distance, standard deviation of mean Euclidean distance, largest patch index, area weighted mean patch fractal dimension and contagion index which is a measure of the landscape heterogeneity describing the extent to which landscapes are aggregated or clumped.

Moghaddam & Samadzadegan (2009) have used CA for urban growth simulation and prediction of Tehran over the last four decades succeeds to test simulated specified growth years at a high precision level, using ArcGIS 9.2. Real data layers have been used in the CA simulation training phase such as 1990 and for testing the prediction results such as 2001. Next step includes running the developed CA simulation over classified raster data for forty years. An ArcGIS extension has been developed to define a set of rules and calibration was carried out based on real urban growth pattern. Uncertainty analysis is performed to evaluate the precision of the simulated results as compared to the historical real data. Evaluation shows promising results represented by the high average accuracies achieved. Some scenarios have been tested and selected a suitable scenario with highest precision. The average precision for the predicted growth images 1975 and 2001 is over 80%. Modifying CA growth rules over time to match the growth pattern changes is important to obtain accurate simulation. This modification is based on the
urban growth relationship for Tehran over time as can be seen in the historical raster data. The feedback obtained from comparing the simulated and real data is crucial in identifying the optimal set of CA rules for reliable simulation and calibrating growth steps.

The employment of CA in urban simulations often entails substantial departures from the original formal structure of CA described by Von Neumann (1951 and 1966), Ulam, Conway (1970), and Wolfram (1983). The great attraction of CA is the fact that many classes of system dynamics can be simulated through it; another important feature of CA is its ability to give equal weight to the importance of space, time and system attributes. The natural ability that CA have to represent complex systems with spatial/temporal behaviors from a small set of simple rules and states made this technique very interesting for geographers and urban researchers. CA are essentially spatial and they are used to model a wide range of phenomena due to its ability to represent spatial process, from forest fires to epidemics, from traffic simulation to regional-scale urbanization, polycentricism, gentrification, historical urbanization, urban growth, form and location. CA-based modeling also allows the integration of socio-economic and natural systems models in a detailed and realistic way.

The three main classes of urban CA models, for three different purposes, not mutually exclusive, that are a direct result of the exploration of modifications of the formal CA as highlighted by Moghaddam & Samadzadegan (2009) are:

(i) Models designed to explore spatial complexity;

(ii) Models designed to research themes of economical, sociological and geographical areas; and

(iii) Models designed to produce operational tools for planning.
The data that has been used for the urban growth simulation included three historical satellite images covering a period of forty years. These raw images include one 60 m resolution MSS image (1975) and four 30 m resolution TM images (1990 and 2001). The images are geometrically rectified to the same projection of Universal Transverse Mercator (UTM) zone 39N. Projected images are registered to spatially fit over each other using a second order polynomial transformation function and 15 well defined control points. Registration errors are very small represented by values far less than one pixel. Six image classes are defined based on maximum likelihood classification system (1976): water, road, commercial, green area where land has been covered by forest area, residential areas and on-urban areas. Commercial and residential classes were combined after the simulation as one class called urban. Ground reference data sources including orthophotographs classification maps are used for identifying the land cover classes and for training and testing data collection. Results indicate high precision level of classification above 75%.

First the oldest classified image 1975 is selected as an input for CA urban simulation. For each growth simulation step, a new empty achromatic raster image with the same size as the input classified image (1975) of 526x526 pixels is created. A 3x3 Moore neighborhood is used in the simulation process. The updated center pixel is determined as a function of current state of center pixel and the states of the neighborhood pixels. The output image of one growth step is used as input for the next growth step to have accumulative urban growth. Ground truth images 1990 is used for training to calibrate the CA rules and growth step while ground truth images of 2001 is used for testing purposes only. The simulated CA image for the first ground truth (1990) is obtained after running the CA algorithm using different scenarios of CA rules and growth steps to accumulate the growth to this date. Growth step and CA rules are calibrated through testing the
scenarios results’ by comparing them to the ground truth of image 1990 and select the growth step and CA rule with minimum simulation error. Once the calibrated step and CA rules are obtained, they are used to run the simulation to predict the growth for year 2001.

Many scenarios are tested to tune the CA rules and investigate the precision of them and the two scenarios used for rules which have got the highest precision to run the simulation from 1975 to 1990 for the updated rules are given below:

Scenario 1:

1. IF tested pixel under consideration is water, THEN no growth is allowed at this pixel.
2. IF tested pixel under consideration is road, THEN no growth is allowed at this pixel.
3. IF tested pixel under consideration is residential OR commercial (Urban), THEN keep this pixel the same without any change.
4. IF center pixel under consideration is (Green Area) AND there are 4 urban pixels in the neighborhood, THEN change center pixel to Urban.

Scenario 2:

1. IF tested pixel under consideration is water, THEN no growth is allowed at this pixel.
2. IF tested pixel under consideration is road, THEN no growth is allowed at this pixel.
3. IF tested pixel under consideration is residential OR commercial (Urban), THEN keep this pixel the same without any change.

4. IF center pixel under consideration is (Green Area) AND there are 3 urban pixels in the neighborhood, THEN change center pixel to Urban.

The simulated image is evaluated based on the following equations and compared to the 1990 ground truth image for updating the rules:

\[
\text{Urban} = (\text{Commercial} + \text{Residential})
\]

\[
\text{Error} = (\text{Urban}_{\text{simulated}}) - (\text{Urban}_{\text{real}})
\]

\[
\text{Precision} (\%) = 100\% - \text{abs}\left((\text{Urban}_{\text{simulated}}) - (\text{Urban}_{\text{real}})\right) / (\text{Urban}_{\text{real}}) \times 100\%
\]

Ward et al (2000) have developed a CA model that simulates local decision-making processes associated with fine-scale urban form for exploring the notion of urban systems as self-organizing phenomenon. The model was integrated with a stochastic constraint model that incorporates broad-scale factors that modify or constrain urban growth. The model was used as a means for simulating the different land-use scenarios that may result from alternative land-use policies and was applied for presenting the possible growth scenarios in a rapidly urbanizing region in south east Queensland, Australia. The authors recall the contributions made by Batty & Longley (1994) who explored the use of cellular models of urban growth in Tauton, England, based on a process of diffusion-limited aggregation and that of Clarke et al (1997) who had been successful in integrating remotely sensed information and CA to develop a model of the historical development of the San Francisco Bay and Washington, DC, areas. In this model the simple rules
of CA are adapted to deal with probabilities of location by incorporating hard constraints, such as topography, road networks, and patterns of existing and historic settlement, that exclude or influence development. Multiple cell states (residential, industry, commercial) are modelled by White et al (1997) using transition potentials on a neighbourhood derived from calibration of the model using historic data on urban growth activities.

The CA model developed by Ward et al (2000) used a Graphical User Interface (GUI) linked to a GIS. The model required three types of spatial information, an initial urban configuration (initial conditions) to seed the simulation run, population projections (boundary conditions for the model) and, constraint data in the form of institutional controls (local government land-use zoning), growth-prohibiting constraints (water bodies, etc.), and growth-modifying constraints (land slope, distance from major and minor road networks, and distance from major commercial centers). Two types of residential growth simulations were developed. In the first, transport network-based growth was used to develop residential growth scenarios from 1988 to 1995 based on detailed knowledge of the 1995 transport network. The second type of simulation is developed with only knowledge of the major transport network and shows growth based on a friction-of-distance neighbourhood for which constraints associated with distance from major roads, distance from population centers and land slope are stochastically realized. Omissions (erroneously excluded elements), commissions (erroneously included elements) and level agreements are calculated to assess the performance of the model. The level of agreement was over 60% in all the simulations.

Mitsova et al (2011) have developed a cellular automata model of urban growth simulation incorporating Markov chain analysis and multi-criteria evaluation techniques for the counties in Ohio, Indiana, and Kentucky
of the United States of America (USA). Two scenarios are examined and compared. The baseline scenario projects urban growth without environmental constraints while the green infrastructure conservation scenario incorporates an open-space conservation network intended to incorporate environmentally significant areas. The transition rules are set up using a multi-criteria evaluation and fuzzy membership functions to develop suitability maps for each simulated land cover class. Five land cover classes were simulated simultaneously.

2.5.6 Advantages and Reasons for Popularity of Cellular Automata

Ward et al (2000) states that models based on, or associated with, CA have recently become popular because of their dynamic behavior and conceptual link with notions of self-organization. These types of models provide effective ways of simulating the process of landscape transformation as well as offering a means of evaluating alternative planning scenarios.

Menard & Marceau (2005) explain that the CA models gain popularity owing to the following reasons:

(i) CA adept at dealing with spatial phenomena. CA makes implicit use of spatial complexity whereas traditional methods tend to abstract from spatial details. CA handles proximal space combining both the relative and the absolute view of space and the absolute views of space through the concept of neighborhood whereas traditional models (location – allocation or economic models) use a relative view. Site and situation are therefore linked in CA;
(ii) Geographers are already familiar with cell representation of CA as it is similar to the spatial characteristics of remote sensing images and raster GIS;

(iii) The process being modeled is entirely encapsulated in the transition rules, allowing the link between the patterns and the underlying process; and

(iv) There is an increasing need for a high level of spatial detail in applications related to decision making processes, and CA satisfy this need.

Itami (1994) gives the following major advantages of cellular automata theory for modelling physical systems:

(i) the correspondence between physical and computation processes are clear;

(ii) CA models are often based on transition rules that are simpler than complex mathematical equations, but produce results which are more comprehensive;

(iii) CA can be modelled using computers with no loss of precision;

(iv) CA can mimic the action of any possible physical system; and

(v) CA are irreducible.

2.6 SCENARIO PLANNING

Smith (Hopkins & Zapata 2007) identifies Herman Kahn, an early user of the term *scenario*, who had employed and developed it while working at the RAND Corporation (a company involved in improving policy and
decision making through research and analysis) during the 1950s and 1960s. In comparison to more conventional planning approaches employed at that time (and still today), “the scenario” provided an “unconventional aid to strategists, arms controllers and others to help overcome barriers to thinking about unprecedented problems”, Kahn saw scenarios as “particularly suited to dealing with several aspects of a problem more or less simultaneously”. This approach is variously called “the scenario approach”, “scenario-based planning”, “scenario decision making”, “scenario thinking”, or simply “scenarios”. Scenario planning aims to offer the important ways that the future could be different from the past.

A scenario set presents an organization with several believable stories about how the future might be different from the past, and in ways that focus on the unique position of the organization in terms of its own history and culture.

2.6.1 Definition of Scenario and Scenario Planning

Hopkins & Zapata (2007) define scenarios as stories about how the world changes and how it will be changing at some future time. Scenarios include the identification of issues and forces shaping communities through conversations with and about multiple actors intersecting with their communities. They describe scenario planning as a way of thinking about the future without trying to predict it.

Smith (Hopkins & Zapata 2007) states that scenarios are closest to simulations, providing a communicable set of structured possible future systems. He quotes the following definition that Microsoft Excel offers for *scenario*:
“A scenario is a named what-if model that includes variable cells linked together by one or more formulas. Before you create a scenario, you must design your worksheet so that it contains at least one formula that’s dependent on cells that can be fed different values”.

For example, one might want to compare best-case and worst-case scenarios for sales in a coffee shop, based on the number of cups of coffee sold in a week.

The Federal Highway Administration and Federal Transit Administration began advocating the use of scenario planning, for which they offer the following definition (Hopkins & Zapata 2007):

“Scenario planning is a process in which transportation professionals and citizens work together to analyse and shape the long-term future of their communities. Using a variety of tools and techniques, participants in scenario planning assess trends in key factors such as transportation, land use, demographics, health, economic development, environment, and more. The participants bring the factors together in alternative future scenarios, each of these reflecting different trend assumptions and trade-off preferences. In the end, all members of the community – the general public, business leaders, and elected officials – reach agreement on a preferred scenario. This scenario becomes the long-term policy framework for the community’s evolution and is used to guide decision making”.
Scenario is distinguishable from a vision and forecast in two ways. First, a scenario is a possible future. A scenario need not be desirable, thus it is not a vision, nor likely, thus not a forecast. Second, a scenario emphasizes a process of change, not just a point in the future. Planners can employ scenarios as a way of discovering unknown or poorly understood interrelationships or use scenarios to engage broader public input into planning processes (Hopkins & Zapata 2007).

2.6.2 Principles of Scenario Planning

Scenario planning rests on the following four principles specified by Smith (Hopkins & Zapata 2007):

a) Taking the long view: This is about looking beyond the next quarter or the next year to consider longer periods of time, such as five, ten, or even more years, in order to allow significant systemic changes to take place.

b) Thinking from the outside in: Returns to the notion of considering forces and factors beyond the control of an organization. Scenario planning begins from the areas outside an organization and then works back into the organization, rather than from the organisation out, as in many other planning activities.

c) Including multiple perspectives: really offers more than mere cumulative returns from bringing in a few experts with new points of view. When done right, the returns can be multiplicative because new perspectives interacting with other new perspectives will often result in very creative and imaginative ideas.
d) Telling stories: makes the lessons, results, and on-going learning from a set of scenarios much more communicative.

2.6.3 Reasons to do Scenario Planning

The main reasons to do scenario planning (Hopkins & Zapata 2007) include the following:

(i) Scenarios provide a way for us to think, then talk about, and ultimately take into account in our decisions how external forces may play out to create the future in which we will find ourselves;

(ii) The scenario approach allows a systematic sorting through of many of these issues, so that we can pin down at least a few of the most important ones; and

(iii) In a way, scenario planning is actually more about the present than it is about the future – but it is about the present in a way that allows us to leave the past further behind than we are otherwise normally able to do.

Scenarios find a wide range of uses not only in planning but also in variety of fields. As Smith (Hopkins & Zapata 2007) points out, a set of scenarios can be used as:

(i) a **decision tool** – “future proofing” a portfolio of activities and proposed actions

(ii) a **prioritization tool** – determining where and how to allocate finite resources

(iii) a **testing tool** – using multiple “settings” to strengthen an existing strategy, innovation, initiative, or priority
(iv) **an oversight tool** – adding perspective and insight to other planning processes

(v) **an integrative tool** – applying judgement to complexity for making sense of the world

(vi) **a generative tool** – producing innovative ideas, programs, products and services

(vii) **a timing tool** – reacting appropriately (i.e., neither over reacting nor under reacting)

(viii) **a scanning tool** – monitoring for deeper shifts in the external environment

(ix) **a proactive tool** – battling reactive demands; facing the future from the front foot

(x) **a conversation tool** – talking about difficult issues in a safe (hypothetical) way.

The actual number of scenarios employed is quite important. Smith (Hopkins & Zapata 2007) explains how four is ideal, though three or five also work well. The disadvantage of five is that they begin to push beyond the number of stories that we can keep in mind all at once, and certainly more than five can too easily lead to more confusion than clarity. Although sets of three scenarios are often used very successfully, practitioners must be aware of the potential serious drawback: Three stories can allow people to slip into a high/medium/low mind set, a future with two bookends. And once in a high/medium/low mind set, people discount the high and the low to focus on the medium, at which point we are actually back to considering a single future, rather than multiple futures. This also holds true for sets of two scenarios, in which one is a baseline and the other the only future of interest. For these reasons, the number of scenarios is in fact quite important, with four
striking a great balance between stretching to multiple futures without presenting an overwhelming number and also steering people away from traditional high/medium/low or baseline-and–desired thinking. However, Deal & Pallathucheril (Hopkins & Zapata 2007) caution that a single scenario need not be selected as preferred and other scenarios need not be discarded. Rather, new scenarios are developed, assessed, and added to a collection that planners then use constantly as a reference as they work on various kinds of planning tasks (developing plans, reacting to other plans) at various scales (from the region down to the neighbourhood scale). The set of futures, rather than a single future, informs their thinking on substantive issues.

2.7 LAND IDENTIFICATION FOR FUTURE

Land use planning is a systematic and iterative procedure carried out in order to create an enabling environment for sustainable development of land resources which meets people’s needs and demands. It assesses the physical, socio-economic, institutional and legal potentials and constraints with respect to an optimal and sustainable use of land resources, and empowers people to make decisions about how to allocate those resources (Food and Agriculture Organisation of the United Nations 1999).

The characteristics of the Land Use Models (Waddell, <http://stepsa.org / resources / shared-documents / urbansim-csir-seminar-presentation>. [08.08.2011]) include the following:

- Create inputs for travel demand forecasting
- Simulate impacts of transportation investments
- Simulate impacts of land policies
- Support integrated land use, transportation, and air quality modeling and planning.
In the Indian context, the land allocation plan for metropolitan areas is carried out by the respective Development Authorities. The Master Plans are prepared by them for metropolitan areas indicating the land use plan for a plan period, normally 20 years. For Chennai Metropolitan Area (CMA) too, the Chennai Metropolitan Development Authority prepares the Master Plan. Presently, the Second Master Plan for CMA-2026, approved under the provisions of the Tamil Nadu Town and Country Planning Act, 1971 is in force since 02.09.2008. It has broadly classified the land use in CMA based on the population projection, under eleven land use zones viz., Primary Residential, Mixed Residential, Commercial, Industrial, Institutional, Special and Hazardous Industrial, Agricultural, Non-urban, Urbanisable, Open Space and Recreational and Other uses. There is no specific mention made in the plan on the strategy adopted for land use planning. Besides land use zoning, the Master Plan has detailed out the various projects and proposals for improvement of transportation network and other infrastructure for the plan period. The Development Regulations for carrying out various construction activities in CMA is also spelt out in the Plan. The Plan has emphasized the need for regular monitoring and review for its success.

2.8 SUMMARY

The review of literature has been carried out under various sections. In the first section detailed study is made on urban growth and the complexity involved in the process of urban growth. It has given an insight as to how the urban growth occurs, the agents involved and the importance of the decisions of the agents in the process of urban growth. The factors which influence urban growth in different urban settlements are studied in the next section. Among the various factors identified in each of those studies, it is seen that the factors like availability of land for development, accessibility to transportation network, proximity to work places, availability of basic
infrastructure facilities, plans and policies governing the development activities have played a vital role in the process of urban growth. The different methods of urban growth modelling were studied in detail. In particular, the elaborate study of cellular automata model and the advantages of application of cellular automata model for simulation of urban land use changes gave the impetus for its adoption in the present research. The benefits of scenario planning underline the necessity of employing it as part of the urban planning process so as to ease the decision making process by the planners and the administrators. In the last section the land use zoning prepared by the government agencies is discussed. The review of literature carried out under various sections has given an insight into the complexity involved in urban modeling and an understanding of the solutions available for overcoming this herculean task so as to manage urban growth.