Nature Environment and Pollution Technology
An International Quarterly Scientific Journal

p-ISSN: 0972-6268
(Print copies up to 2016)
e-ISSN: 2395-3454

Vol. 22 | No. 3 | pp. 1251-1265 | 2023

Original Research Paper

https://doi.org/10.46488/NEPT.2023.v22i03.013

Open Access Journal

Land Use Land Cover (LULC) Dynamics by CA-ANN and CA-Markov Model Approaches: A Case Study of Ranipet Town, India

Malathy Jayabaskaran and Bhaskar Das†
School of Civil Engineering (SCE), VIT, Vellore, Tamil Nadu, India
†Corresponding author: Bhaskar Das; bhaskar.ju@gmail.com

Nat. Env. & Poll. Tech.
Website: www.neptjournal.com

Received: 20-12-2022
Revised: 21-02-2023
Accepted: 01-03-2023

Key Words:
LULC
Industrialization
Land degradation
Probability approach
CA-ANN
CA-Markov

ABSTRACT

The present study analyzed the spatio-temporal variations in the Land Use Land Cover types within Ranipet Municipal town in Ranipet District, Tamil Nadu State, India, using two different platforms (QGIS and IDRISI Selva v.17.0). The possible parameters driven the net changes in the Land Use Land Cover (LULC) types were also incorporated for the analysis. Results revealed the positive net changes in the built-up area are about 26.8%, and combined other classes like vegetation, barren land, and water bodies have net negative changes during 1997-2019. Particularly barren land was found to have a reduction of 17.4% due to the massive industrialization in the study area. Further, the LULC maps were used for future prediction (2029) using the dynamic models of CA-ANN (Cellular Automata and Artificial Neural Network) and CA-Markov. Predicted maps yielded a kappa index of 81.6% and 82.6% for CA-ANN and CA-Markov, representing their respective accuracy levels. The CA-Markov model is extended for determining the probable long-term changes for 2080 in LULC with a kappa index of 76.2%. Compared to the CA-ANN model using the QGIS platform, CA-Markov provided better analysis, particularly from one cell to the other. According to the survey and the ground truth in the locality, industrialization and occupational shift were the most influential drivers of LULC dynamics. Moreover, the results of this study assist the stakeholders in the decision-making process for future sustainable land use management.

INTRODUCTION

Land Use Land Cover (LULC) provides substantial ecosystem services and greatly impacts landscape patterns and long-term ecological sustainability (Muyibul et al. 2018). The LULC dynamics delineates the transformations from one land use class to another for two different periods due to the human activities on the earth's surface (Lambin et al. 2001). Alteration of LULC results in landscape homogenization and fragmentation of natural habitats (Muyibul et al. 2018) and destabilize the pattern of ecosystem services (Sutton et al. 2016). Encroachment on natural habits is a very common issue in rapid urbanization due to industrialization or other developmental motives, which leads to land degradation through deforestation, soil compaction, water and soil salinity, disposal of untreated waste on land, etc., on the local and global scale (Geist & Lambin et al. 2004, Reynolds & Smith 2002, Romm 2011, Bucx et al. 2010). Hence LULC dynamics become an essential component of monitoring and quantifying climate change, biodiversity, hydrology, and air pollution (Sellers et al. 1995, Bonan 2008, Butchart et al. 2010, Schröter et al. 2010) to minimize the effects of human activities on the environment (Tripathy & Kumar 2019, Norman et al. 2009).

Recent advancements in remote sensing (RS) and Geographical Information Systems (GIS) have proven to be effective tools for studying LULC dynamics by acquiring, analyzing, and quantifying data rapidly and regularly at lower cost and time than traditional ground survey methods (Mishra & Rai 2016). The suitability of RS and GIS in LULC dynamics has led to the evolution of several geospatial models to simulate and predict future spatial-temporal patterns and act as decision-support tools (Wang & Maduako 2018). Most of these models work based on a probability approach simulating and predicting the land use changes for any location (Verburg et al. 2004), and their outcomes have been proven to be effective tools for future planning and land use management and also in evaluating the land use policies (Turner et al. 2007). Based on the recent literature, some of the most popular models are CA (Berberoğlu et al. 2016, Jat et al. 2017, Mustafa et al. 2017), ANN model (Mozumder & Tripathi 2014, Maithani 2015), regression models (Nong & Du 2011), Markov chain (Arsanjani et al. 2011, Al-Sharif & Pradhan 2014), CA-logistic regression models (Arsanjani 2012, Mustafa et al. 2018), CA-Markov models (Arsanjani et al. 2013, Mondal et al. 2016) and CA-ANN Model (Rahman et al. 2017, Gantumur et al. 2020), etc. Many kinds of literature have also discussed individual models' limitations (Araya & Cabral 2010, Balzter 2000, Triantakonstantis & Mountrakis 2012). Among the existing models, CA is the simplest and most popular open structure model capable of intercepting the spatio-temporal dynamics of LULC. This model is flexible, can be integrated with multiple techniques, and is best suited at the micro level (Aburas et al. 2017, Tripathy & Kumar 2019)). Markov Chain is a stochastic modeling approach that also can be used conveniently to study and simulate LULC trends in short-term projections. One limitation of this model is that it does not intercept and simulate spatial trends in LULC (Rahman et al. 2017, Mishra & Rai 2016). Combining CA with Markov techniques can efficiently be applied for a large area with spatial-temporal interpretation, thus overcoming their limitations (Gantumur et al. 2020, Keshtkar et al. 2015, Rimal et al. 2017). The artificial neural networks (ANN) system model is vaguely inspired by biological neural networks, which effectively simulate multiple land-used changes in complex non-linear environments (Saputra & Lee 2019, Mishra & Rai 2016, Pijanowski et al. 2002). The details of methodologies adopted in these models are mentioned in the Material and Methods section.

The present study aims to understand and simulate the changes in LULC of a Ranipet Municipal town in the Raipet district of Tamil Nadu state. The municipality includes the Ranipet industrial area, one of India's biggest exporting centers of tanned leather. The total number of tannery industrial units in and around this town is 240, besides industrial hubs like Bharat Heavy Electrical Limited (BHEL) and State Industries Promotion Corporation of Tamil Nadu Limited (SIPCOT) of other industries like ceramic, refractory, boiler auxiliary plant, and chromium chemicals. This is also the place of TCCL (Tamil Nadu Chromate and Chemicals Limited), which operated from 1975 to 1995, mainly producing chromium bichromate, and basic chromium sulfate, reagents required for the chemical processing of leather. After its closure in 1995, it was reported to have 2.27 Lakh tons of chromium-bearing solid waste got accumulated and dumped at the premise (TNPCB 2010). Ranipet industrial town was considered one of the world's worst polluted places by the New York-based Blacksmith Institute (BI) in 2007 (http://www.blacksmithinstitute.org/). The history of pollution in Ranipet is more than two decades older, raising Public Interest Litigation (PIL) by Vellore Citizens' Welfare Forum vs. Union of India (1996). The petition was filed against the discharge of untreated effluent sewages, which consist of 170 types of chemicals, by more than 900 tanneries in Vellore. The large-scale land and water degradation had been reported to have affected 35,000 hectares of land (Vellore Citizens' Welfare Forum 1996). There is a limited number of reports concerned about the extreme heavy metal like Cr, Pb, Ni, Zn, and Cd contamination in groundwater and lake water (Srinivasa Gowd & Govil 2008, Rao et al. 2013), problems associated with the partially treated solid and liquid waste (Rao et al. 2011, Mandal et al. 2011) and bioaccumulation of heavy metals in indigenous plant species (Vidya et al. 2010) from the study area. But there is no available study on the spatio-temporal dynamics of LULC due to unplanned human interventions in this vulnerable town. Rapid industrialization has triggered the change in LULC, eventually leading to land and water degradation in the study area. Hence, the study of LULC dynamics will bridge the gap of available scientific data required to accurately assess the pollution trend and plan for a holistic mitigation approach. Based on the above discussion, the present study's scope is (i) to analyze the spatial-temporal variations in the Land Use Land Cover of Ranipet Municipality, Ranipet district, Tamil Nadu state for two decades. (ii) to simulate and predict the future changes in LULC for the year 2029 using the CA-ANN model (iii) to predict the LULC changes for 2029 & 2080 using IDRISI Selva v.17.0 and comparing the results with the CA-ANN model (iii) to explain the impacts of LULC in Ranipet and the drivers influenced for the change with due consideration to socio-economic factors.

MATERIALS AND METHODS

Study Area

Ranipet is a Municipality in Ranipet district (formed by trifurcating erstwhile Vellore district in 2019) which lies in the North Latitude of 12°55'0" to 12°58'0" and East Longitude of 79°17'30" to 79°17'30" and falls in the survey of India Toposheet No. 57-P/5 (Fig. 1). This bustling industrial hub is situated 116 km from Chennai, the capital city of Tamil Nadu state, and 43 km before the Chittor district of Andhra Pradesh. It is sited in Plot 25 of SIPCOT Industrial Estate along the NH- 4 Ranipet, TN. The study area is surrounded by hillocks on the northern and western sides. The southern side of the location is a Pedi plain. The major source of drinking water is the Palar River, which runs from west to east and is located 4.5 km downstream of the side. The area falls under the moderate to high rainfall zone, receiving 1000mm rainfall annually from South-West and North-East monsoons. The rapidly growing large and small-scale industries like leather and leather-based industries, pharmaceuticals, and other chemical factories and their pollution levels, groundwater, and soil contamination are the primary reasons for choosing Ranipet as the study area.

Data and Pre-Processing

The required images for the study of land use land cover

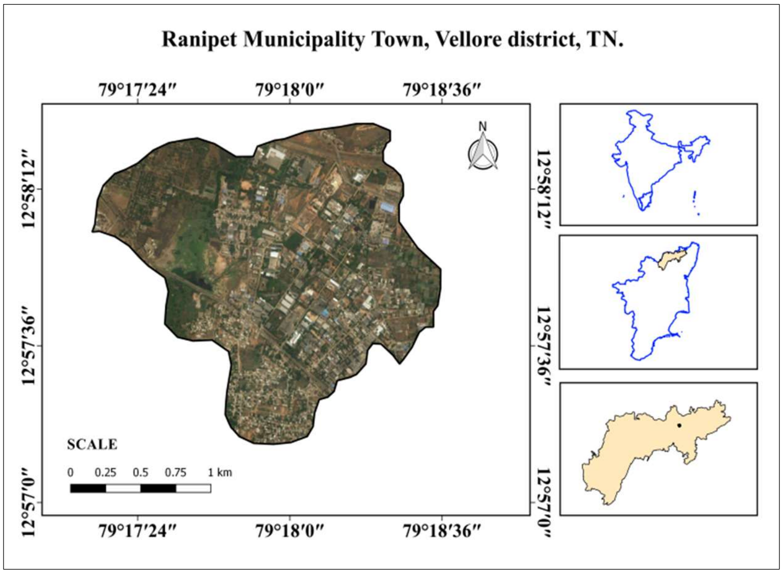


Fig. 1: Ranipet – Study area of the given study.

changes of the location were obtained and downloaded from the official USGS website (https://earthexplorer.usgs.gov/). Landsat Thematic Mapper (TM) remote sensing images were used as the basic data, and relatively the images are free from the cloud cover (Vasconcelos et al. 2015). The satellite image details used in the study are shown in Table 1. The Landsat images were geometrically corrected to UTM (Universal Transverse Mercator), Zone 44 North, and WGS 84 (World Geodetic system 84) datum, with a spatial resolution of 30m. Images were classified by visual interpretation.

The initial land use land cover (LULC) types were classified into four basic and primary types: settlements, vegetation, barren land, and water bodies. The details are shown in Table 2. Data regarding the population and GDP were taken from the census 2001-2011 handbooks. These parameters were used to determine the driving forces of the land use land cover in the study area (Pan et al. 2012). Fig. 2 shows the methodology adopted for carrying out the entire study. It clearly explains the two methods, CA-ANN and CA-Markov are the models used to predict the LULC for 2029 and 2080. QGIS open source Platform is used to study the land use and land cover of the study area since it has less processing time and better rendering capabilities. Here in the current study, the QGIS platform has been used to follow the CA-ANN model. To adopt CA-Markov for future prediction, IDRISI Selva v.17.0 interface has been effectively utilized for ease. The Land Change Modeller (LCM) in the IDRISI interface uses machine learning procedures to analyze historical land cover data to model the future. LCM uses Markov Chain analysis to project the expected quantity of

Table 1: Satellite data specifications.

Sensor	Path	Row	Spatial resolution (m)	Acquisition Year
Landsat 4/5 Thematic Mapper (TM)	143	51	30	1997
Landsat 4/5 Thematic Mapper (TM)	143	51	30	2009
Sentinel 2	-	-		2019

Table 2: Classification of Land Use Land cover.

LULC class	Description
Settlements/Built up area	Residential, commercial, and industrial services, transportation networks, socio-economic infrastructure, and urban and rural settlements.
Vegetation/Cultivated land	Agricultural area, crop fields, cultivated area, and vegetable lands.
Barren land/Uncultivated land	Exposed soils, open fields, landfills, and sand fill areas.
Water-bodies	Rivers, lakes, ponds, perennial water bodies, and reservoirs

change and a competitive land allocation model to determine scenarios for a specified future date.

Cellular Automata – Artificial Neural Network (CA-ANN) Model

Some of the earliest approaches of CA models to simulate and predict LULC dynamics are developed by Couclelis (1985), Batty & Xie (1994) and White & Engelen (1994). Later, many utilized it for modeling and predicting present and future spatial and geographical changes (Mishra & Rai 2016, Halmy et al. 2015, Arsanjani et al. 2013).

The principle behind the model is that the change in the land use of any cell could be defined by the present state and the changes in the adjacent neighboring cells (Koomen & Borsboom-van Beurden 2011). With this cellular Automata (CA) model, when ANN was integrated, there would be sound improvement in the simulation and future predictions (Li et al. 2001, Pijanowski et al. 2002). In this work, the extensively used CA-ANN model is used to predict the future (2029) land use land cover changes using multiple satellite images of 1997, 2009, and 2019 as input parameters.

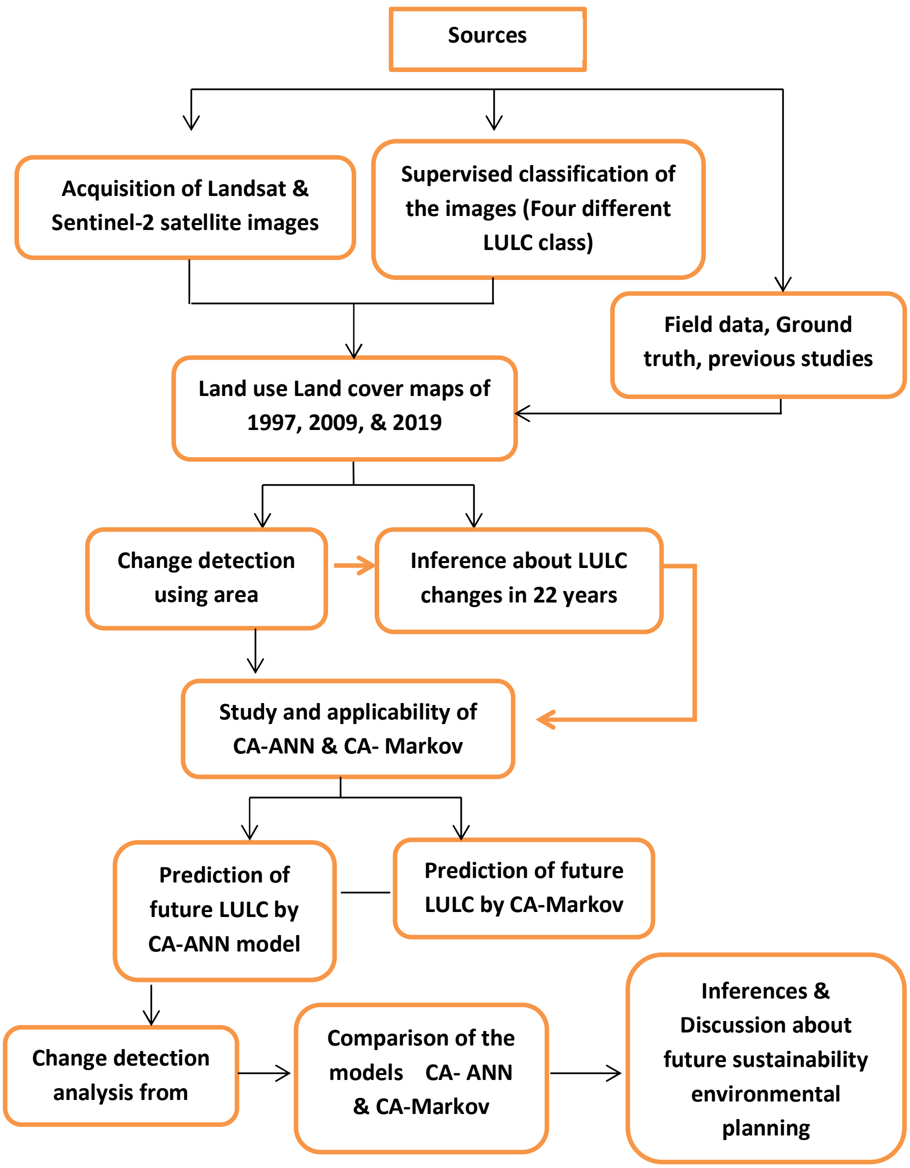


Fig. 2: Flow chart for the current study.

The Markov Model

To model and predict the changes in land use and to understand the future land development in any area, Markov models are widely used (Parsa et al. 2016, Subedi et al. 2013). Also, it is used in ecological modeling and other land-based simulations. The mathematical equation (eq. 1) helps calculate the required future land use changes.

$$L\,(t, t+1) = P_{ij} * L\,(t) \quad ...(1)$$

Where L(t) and L(t+1) represents the corresponding land use status at time t and t+1 respectively, P_{ij} represents the transition probability matrix in a given state.

$$P_{ij} = \begin{bmatrix} P_{11} & P_{12} & \dots & P_{1n} \\ P_{21} & P_{22} & \dots & P_{2n} \\ \dots & \dots & \dots & \dots \\ P_{m1} & P_{m2} & \dots & P_{mn} \end{bmatrix} \quad ...(2)$$

$$(0 \le P_{ij} \le 1)$$

Where 'i' is the current state and 'j' represents the next state (one period to the other). The cells in the transition matrix range from zero to one. A higher value close to one indicates a high transition probability, and a lower value close to zero predicts a lower transition probability. Two LULC images are processed to determine transition probability and area matrices through the Markovian chain (Mishra & Rai 2016). These models are effectively used when the socioeconomic factors influencing the change are difficult to represent (Turner et al. 1989).

Cellular Automata – Markov Chain model

To simulate and predict the changes in the LULC, the CA-Markov model was more advantageous since it integrated both the cellular automata and Markov chain (Singh et al. 2015, Parsa et al. 2016). The transition probability matrix can be found by cross-tabulating two satellite images for two periods (Singh et al. 2015). CA-Markov model is a strong and powerful method in LULC dynamic modeling where any spatial characters also could be incorporated into the model (Singh et al. 2011, Wang & Maduako 2001). This model helps simulate the two-way transitions between classes for several periods (Poutius et al. 2005, Ye et al. 2008). Remember, Cellular Automata (CA) is a common dynamic model which is been used for several years to determine the spatio-temporal changes for any location. Every cell value in the matrix will represent the land area and its growth actions since they are dynamic (Brown et al. 2004). The prime advantage of the model (CA) is that it clearly explains the dynamics of the classes despite the dependency on the neighboring cell values. The expression of the CA model is as follows (Subedi et al. 2013, Sang et al. 2011).

$$L(t, t+1) = f(L(t), P) \quad ...(3)$$

Here L(t, t+1) represents the class status at time (t, t+1),

$$Contiguity\ filter\ 5x5 = \begin{bmatrix} 0 & 0 & 1 & 0 & 0 \\ 0 & 1 & 1 & 1 & 0 \\ 1 & 1 & 1 & 1 & 1 \\ 0 & 1 & 1 & 1 & 0 \\ 0 & 0 & 1 & 0 & 0 \end{bmatrix} \quad ...(4)$$

To state the neighborhood of each cell on a suitability image, a contiguity filter of size 5 × 5 pixels is used. This standard filter has a cellular space which helps gain a class to occur near where the class already existed. Furthermore, it helps to eliminate the unknown changes that might occur in land use land cover (Ahmed & Ahmed 2012).

RESULTS AND DISCUSSION

Landscape Dynamics

A supervised classification was performed using raw satellite images to know the study area's land use and land cover dynamics. Two different platforms, say QGIS platform and IDRISI Selva v.17.0, were used to identify the spatio-temporal dynamics to obtain accurate changes. Likewise, a detailed analysis was carried out to identify the key variations and drivers influencing the LULC changes. The Land Use Land Cover (LULC) classified images for 1999, 2009 and 2019 are shown in Fig. 3, representing four major settlement classes: barren land, water bodies, and vegetation cover. The corresponding percentage area changes for 1997, 2009 & 2019 are represented in Fig. 4. A detailed discussion of the change in the four major classes is in the subsequent sections.

Change in the Barren Land

Barren land refers to exposed soils, unoccupied land, uncultivated area, open fields, landfills & sand fill areas. In this study area, overall barren land covered up to 37.8% in 1997. This may be due to the initial evolution period of industries like leather and leather-based, chemical, pharmaceutical, and ceramic factories. Noticeably, in the next ten years (1997-2009), there was a steep decline in the percentage of open fields from 37.8% to 21.7%. This date gives a clear picture of the sudden growth of large and medium-scale industries in Ranipet municipality, which reduced the percentage of open fields and made the other LULC type (settlement) grow. It is also important to know that the Small industries promotion corporation of Tamil Nadu (SIPCOT) and Small Industries Development Corporation of Tamil Nadu (SIDCO) Industrial complexes were established

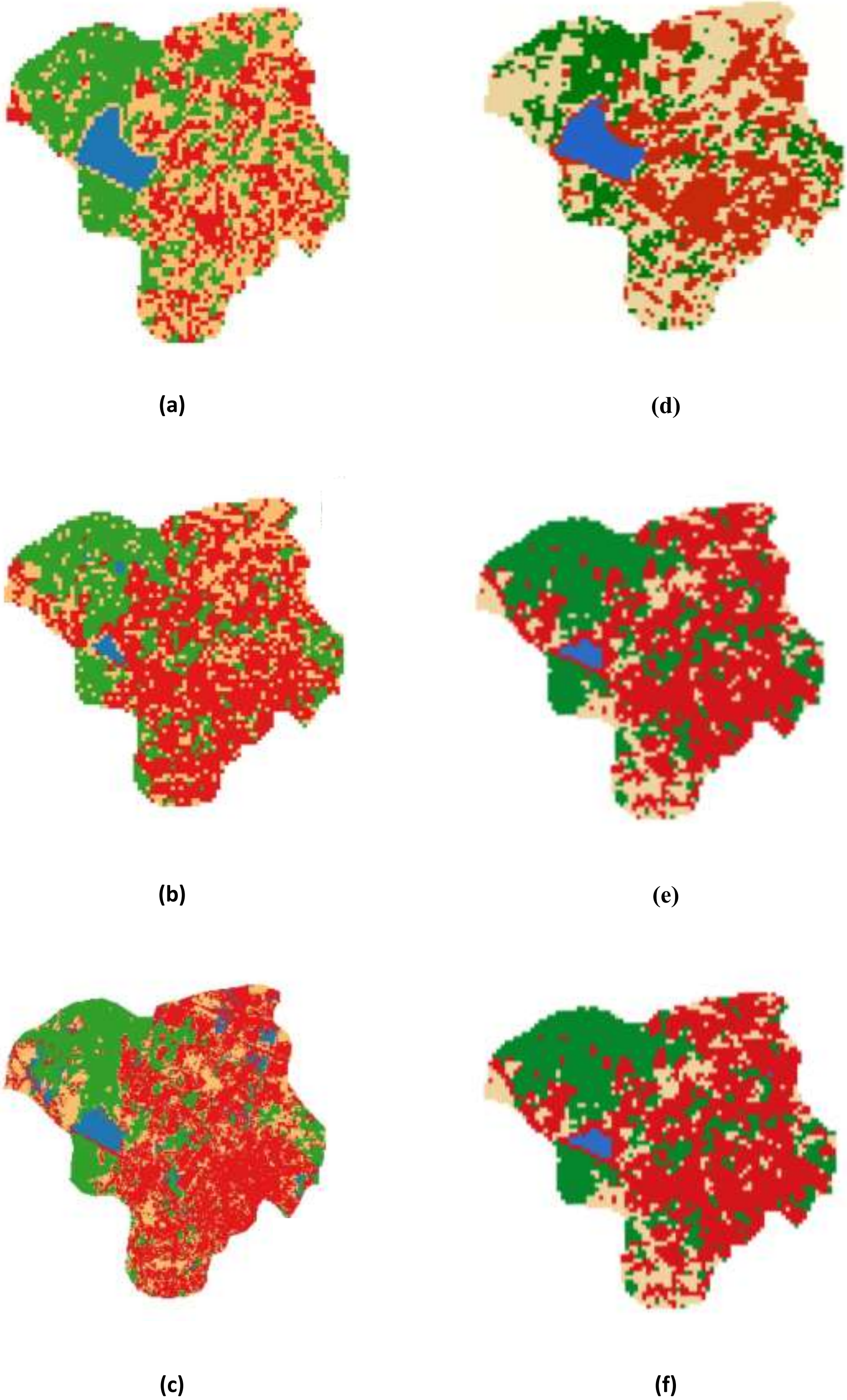


Fig. 3: Land use/Land cover classification of the study area for 1997, 2009 and 2019 using CA-ANN and CA-Markov models.

in Ranipet in the 18th century by the government of Tamil Nadu for the massive economic development of the state.

This may be one of the reasons behind the drastic reduction in the year 1997-2009. Further reductions say 1.22% of the total area in the barren land, were observed for the next consequential decade, 2009-2019. But there is no significant reduction as it happened in the earlier decade. We must consider the growing number of small-scale industries during the 19th century. The minor change in the barren land in the 19th century did not affect the economic development of the municipal town. Instead, it increased. The immense difference in the 18th century made drastic industrialization and settlements in the study area. Ministry of Micro, Small and Medium Enterprises (MSME: 2015-16) reports that the shift from barren lands to settlements made Ranipet town the top 10 contributors to the state's GDP.

Change in Settlements/Built Area

Built-up areas or settlements refer to residential, commercial, and industrial services, transportation networks, socio-economic infrastructure, and urban and rural settlements. The LULC analysis on the QGIS platform revealed a sharp increase in the settlement class from 1997-2009. The settlement covers about 23.28% in 1997 and 48.74% in 2009. The percentage change in this decade is 25.456% which is very drastic within 10 years. This helps us understand the growth of the second-grade municipality to a first-grade municipal town, Ranipet. The increasing trend in the settlement is due to the local employment opportunity available in the area because of the massive industrialization in the 19th century. Also, the road and railway network was fully established (NH-4: Chennai-Bangalore Highway in the early 19th century) for transporting men, goods, and other easy movements of essential commodities to the industries. Settlement cover in 2009 and 2019 is about 48.74% and 50.1%. There is no profound change in the settlement cover in the latter decade, but only a smaller gradient of change, i.e. 1.257 %, is observed. It also can be seen in the LULC change map in 2019 that the area between the road and railway network has increased in the past 20 years.

Change in the Vegetation Cover

Vegetation cover refers to agricultural, crop fields, and cultivated areas. The land use land cover analysis revealed a reduction in the agricultural area from 33.05% to 27.59% during 1997-2009. Trivial alterations could be tallied with respect to the pre and post-monsoon conditions since the satellite images were collected between January 1997 and August 2009. The decreasing trend during this decade may also be due to the establishment of Phase I and Phase II industrial complexes of SIPCOT, Ranipet, by the Government of Tamil Nadu. Further, the trend is declining up to 2.7% in the next decade (2009-2019), which gives a real picture of the industrial clustering in the study area. Visible agricultural cover can be seen on the southern and eastern sides of the location in the land use land cover maps.

Change in the Water Bodies

Water bodies refer to perennial rivers, lakes, ponds, and reservoirs. It can be seen from the land use land cover map of Ranipet in 1997 that there are so many visible water bodies that contributed 4.84% of the total area, but in 2009, it was observed that there is a steep declining trend in the water bodies, about 1%. Almost a decrease of 2.7% is observed from the LULC data. This may be due to (i) over-exploitation of the surface water bodies by the nearby large and medium scale industries for leather processing and finishing, (ii) Satellite maps of 1997 and 2009 are collected from two dissimilar periods, say January and August. It should also be understood that rainfall plays an important role in the change in the percentage area of the water bodies. Likewise, increased settlement area in the earlier decade (1997-2009) may contribute to the change of water bodies.

Table 3: Transitional probability matrix of LULC change.

Transition period	LULC types				
	To	Barren land	Settlements	Vegetation	Water bodies
1997-2009	Barren land	0.2533	0.5647	0.1791	0.0028
	Settlements	0.1932	0.7397	0.0659	0.0011
	Vegetation	0.2106	0.2570	0.5252	0.0072
	Water bodies	0.1257	0.3443	0.3989	0.1311
2009-2019	Barren land	0.2901	0.4848	0.1678	0.0572
	Settlements	0.2059	0.6869	0.0716	0.0355
	Vegetation	0.1386	0.1967	0.6262	0.0384
	Water bodies	0.1370	0.3136	0.1963	0.3531

The latter decade (2009-2019) does not show a decreasing trend, instead, there is an increasing gradient from 1% to 4.77%. Fluctuations in the surface bodies may also have other environmental reasons.

LULC Change Pattern in 22 Years (1997-2019)

The spatial maps were developed and studied thoroughly to understand the overall land use and land cover change from 1997-2019 (22 years). The analysis revealed the major shift in the [1]9th century concerning the classification types like barren land and settlement cover. The primary reason behind the major changes from barren lands to settlements may be the growing industrialization and the economic development of the Ranipet municipality. Within ten years, from 1997-2009, the change in the settlement cover is observed as 26.8% of the total area. The major reason behind the massive industrialization in Ranipet municipality is its proximity to the Palar River, a major perennial river in Tamil Nadu state. No predominant change was noticed in the water bodies from 1997 to 2019. But there is a noticeable decline in the vegetation cover from 1997-2019. The shift might be either from vegetation cover to settlement/Barren land. The area's economic development and industrialization lifted the employment opportunities, which attracted the local people to work for the industries.

The transition matrix in Table 3 properly explains the trend in the LULC change. The values in the matrix reveal the chances or likelihood of getting transformed from one LULC change to the other. The transition probability values are for 1997-2009 and 2009-2019. The LULC classifies images for 1997, 2009 & 2019 used in the QGIS platform (MOLUSCE plugin). The value in the cell reveals that the probability is very high in the case of settlements compared with any other classes. In both consecutive decades, the probability of getting transformed into settlements is high. About 26.8% of the total area has transformed into settlements from 1997-2019. No other classification type has witnessed this drastic transformation except settlement. Changes in the LULC from 1997-2019 in Ranipet Municipal Town are critically influenced by many drivers such as population, number of industries, local workers' occupational dependency, agriculture & livelihood, and economy. The detailed discussions on the major drivers for the LULC change are in the following sections.

Perceived Drivers of LULC Change

Industrialization

As per reports, Ranipet town is a protracted polluted area, one of the biggest exporting centers of tanned leather (NGRI studies). The state government selected this town to establish SIPCOT and SIDCO industrial complexes in 1973 since it is 3.5 km from the River Palar and NH-4 (Chennai-Bangalore Highway). The numbers of tannery industrial units in and around the town are almost 300, besides other industries like Chromium chemicals, petrochemicals, pharmaceuticals, drugs, foundry, boilers, refractories, auxiliary plants, and Heavy engineering. As per Tamil Nadu Pollution Control Board (TNPCB) reports in 2010, 123 leather-based industries, including chemical, galvanizing, paint, and rubber, fall under the category (Highly Polluting and hazardous). Besides this, 167 industries, like dry tannery processing, light engineering, plastic products, leather boards, pulverizing, etc., fall under the orange and green category in Ranipet town. Industries like Tamil Nadu Chromate Chemicals Ltd (TCCL), Thirumalai Chemicals Ltd (25B), Malladi Drugs & Pharmaceuticals Ltd. (I & III, 7C), and SVIS Labs were categorized as highly polluting industries by TNPCB in 2010. The SIPCOT industrial complexes (phase I & II) are surrounded by four villages such as Agraharam (North), Vanapadi (East), Karai (South) & Puliyankannu (West). The respective population in these villages as per Census: 2001 are 10628, 3971, 5344, and 4777, respectively. The population increase since 2001 is 7.45%, and the number of large and medium-scale industries in Ranipet town has increased from 143 to 240. Apart from this, 158 footwear-based industries and 27 leather goods-based industries were also identified. The local people found employment in the above-mentioned industries, and the total number of workers in each category was 2700, 1986, & 18249, respectively (Statistical Handbook, Vellore district, 2016-17). Small-scale industries based on leather-related products were 392 (registered) and 372 nos' in chemicals and chemical products. People dependent on these industries are 14018 & 2050, respectively, in 2016-17. Due to the greater economic lift and massive industrialization from 1980 to 2019 in Ranipet, the district became one of the ten top contributors to the GDP of the state (MMSME, 2015-16 survey). There is an occupational shift from the agricultural sector to the industrial sector solely because of the increased income. The massive shift from barren land to settlement also confirms the industrialization in the past 20 years.

Agriculture and Livelihood

In the 1960s, the main occupation in Ranipet was agriculture. Later in the 1970s, the establishment of the industrial complexes of SIPCOT and SIDCO took place by the state government. Still, few are involved in agricultural -work in the town. Major crops like paddy, sugarcane, maize, groundnuts, and other pulses are cultivated in the area. Palar River is the major water source running from West to East, and Pulianthangal, Karai, Vanapadi, Thandalam, and Puliyankannu are the major surface water bodies within the location. The local people in surrounding villages depend on these water bodies for agriculture and other domestic purposes. Industries in the town are liquidating their effluents on the open land and in the major water bodies (Srinivasan Gowd & Govil 2008). Since Ranipet is located on the River Palar, the effluents/leachate, as a runoff, move downstream and worsen the soil and water quality. LULC maps reveal a reduction in the agricultural area from 1997-2019. The drivers behind the reduction of 8.33% of the total area may be due to (i) the adverse industrial pollution in the town, (ii) increased income, and the occupational shift from agriculture to industrial employment. The cultivators and the agricultural laborers are 9.10% and 15.20%, whereas the main industrial workers are found to be 56.17% (Statistical Handbook, Vellore district, 2016-17).

Prediction and Comparison of LULC Change Using CA-ANN and CA-Markov for 2029

One of the major objectives of the work is to predict and understand the future LULC (2029) changes in the Ranipet town using CA-ANN in the QGIS Platform and CA-Markov model in IDRISI Selva v.17.0, respectively. The Cellular Automata – Artificial Neural Network (CA-ANN) and Cellular Automata – Markov models are different models implemented to simulate and predict the Land Use Land Cover Change (LULCC) pattern. Also, the above-mentioned models could be used to produce the probable transition of a cell from one period to the other (1997-2029). The models use the projected recent classified images (1997/2009/2019) to predict the future of 2029. Furthermore, the models analyzed and predicted the spatial changes from 1997-2029, and the corresponding percent area transformations can be observed in Table 4.

Distances from the nearby main roads (NH-4) are the primary variable in predicting the LULC for 2029. The observed value from the transition matrix specifies the probable increase or decrease in the land use classes for 2029. From Table 4, the CA-Markov and CA-ANN values could be compared for further analysis, and the effectiveness of the models could be understood. The transition values from class BL – BL in CA-Markov and CA-ANN are observed to be 0.0420 & 0.9804. The probable transition chances for a class BL in the near future (say 2029) would reduce, particularly for an industrialized town like Ranipet. In this transition, CA-ANN shows a higher value than the other model.

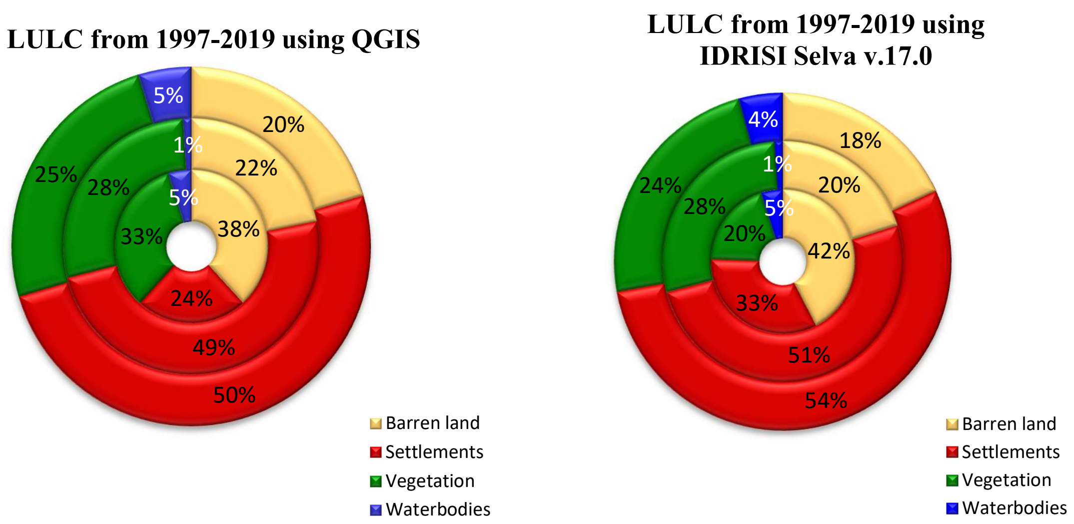
Moreover, the transition value from the class BL – SET are 0.2752 & 0.0196, respectively, for the two models. It is implicit that the settlement should increase substantially with respect to the increase in time. But here, in this prediction, the CA-ANN model gives an underestimated value of 0.0196. The model's effectiveness could finally be agreed upon from the other two classes' transition values of the foresaid models. The transition values from the class BL-VEG, BL-WB, SET-SET, VEG – sets are 0.2468, 0.4360, 0.3749 and 0.2392 for CA-Markov and 0, 0, 0.9956 & 0.0081 for CA-ANN respectively. The predicted values using CA-ANN showed no significant changes in land use classes. Average changes in settlement, vegetation, and barren land are recorded to be 0.01 sq. km only. There is no change in the class water bodies in 2029 using CA-ANN. However, the analysis and prediction performed using CA-Markov showed significant changes compared to the former model. The overall kappa accuracy of the model was found to be 81.58%. The predicted spatial map and the comparison of the predicted land use changes are shown in Fig. 5. The prediction might be more accurate if more spatial variables are incorporated, like rainfall, mean surface temperature, and socio-economic factors in both models.

Prediction and Comparison of LULC Change using CA-Markov for 2080

The CA-Markov model predicts the future LULC change easily and more accurately than the CA-ANN model. But as mentioned earlier, considering and giving equal weightage

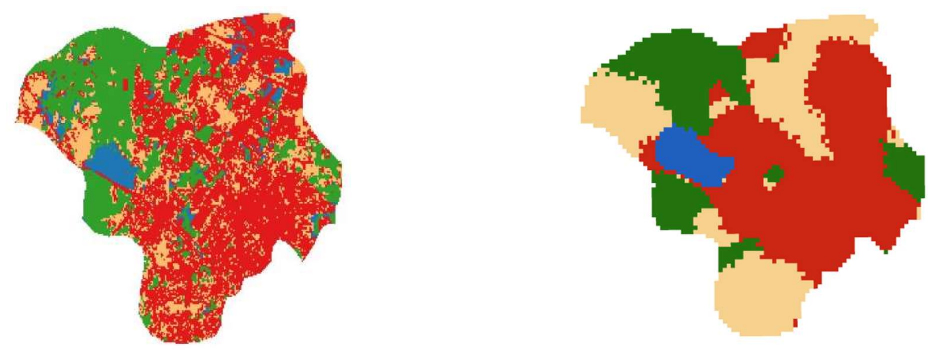
Table. 4: Transition probability matrix of LULC from 1997-2029 using CA-ANN and CA-Markov.

Transition period	LULC types				
	To	Barren land	Settlements	Vegetation	Water bodies
1997-2029 (CA-Markov)	Barren land	0.0420	0.2752	0.2468	0.4360
	Settlements	0.0003	0.3749	0.2181	0.4067
	Vegetation	0.0002	0.2392	0.3584	0.4022
	Water bodies	0.0002	0.3046	0.2421	0.4531
1997-2029 (CA-ANN)	Barren land	0.9804	0.01958	0.0000	0.0000
	Settlements	0.0011	0.9956	0.003117	0.0000
	Vegetation	0.0000	0.0081	0.9871	0.00487
	Water bodies	0.0000	0.0000	0.0000	1.0000

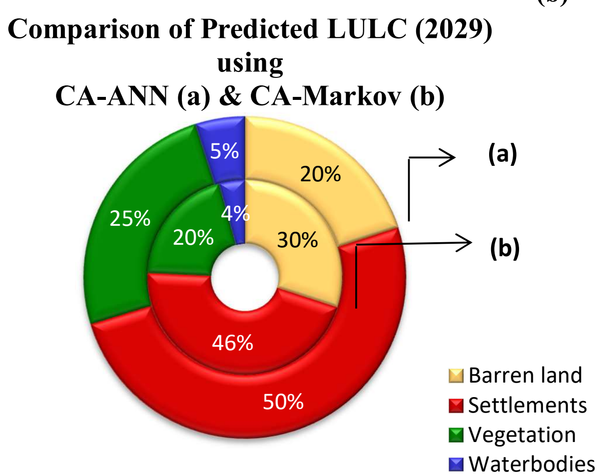


(a) (b)

Fig. 4: Percentage contribution of LULC types for 1997, 2009 and 2019 - (a) Using CA ANN (b) CA-Markov model.



(a) (b)



(c)

Fig. 5: Predicted LULC map of Ranipet area for the year 2029 using (a) CA-ANN (b) CA-MARKOV (c) Comparison of the two models for 2029.

Table. 5: Percentage change in the area from the year 1997-2080 using CA-Markov.

Land Use Type	Change in percentage				
	Present state			Predicted future	
	1997-2009	2009-2019	1997-2019	20019-2029	2019-2080
Barren land	-22.28	-1.98	-24.26	-12.40	-8.04
Settlements	17.65	3.19	20.84	12.58	13.65
Vegetation cover	8.42	-4.30	4.11	0.42	-5.35
Water bodies	-3.78	3.10	-0.69	-0.60	-0.26

Table 6: Transition probability matrix of LULC from 1997-2080.

Transition period	LULC types				
	To	Barren land	Settlements	Vegetation	Water bodies
1997-2080 (CA-Markov)	Barren land	0.2171	0.3021	0.4712	0.0096
	Settlements	0.1718	0.4037	0.4190	0.0055
	Vegetation	0.2005	0.3391	0.4522	0.0081
	Water bodies	0.1889	0.3647	0.4394	0.0069

to the factors influencing the dynamics would produce more accurate results. In this study, the future LULC for the year 2029 is predicted and extended to 2080 by the CA-Markov model. The overall kappa indices of the CA-Markov model are found to be 76.2%. The extension of the work is based on the area changes and transitional probability matrices of the earlier classified images.

Table 5 shows the percentage change in the area from 1997-2080 using the CA-Markov model. It could be observed from the table that there will be an 8% reduction in the class BL and an almost 4% increase in the class SET in the locality from 2019-2080. Only a minor reduction could be seen in the class VEG and almost negligible changes are observed in class WB for the same period. This could be clearly understood from the transition probability matrix shown in Table 6. The predicted images and the percent land changes can be seen in Fig. 6.

The cubic spatial trend in the transformation of land use class to the other using IDRISI Selva.17.0 could be observed in Fig. 7. The values close to one represent the growth, and

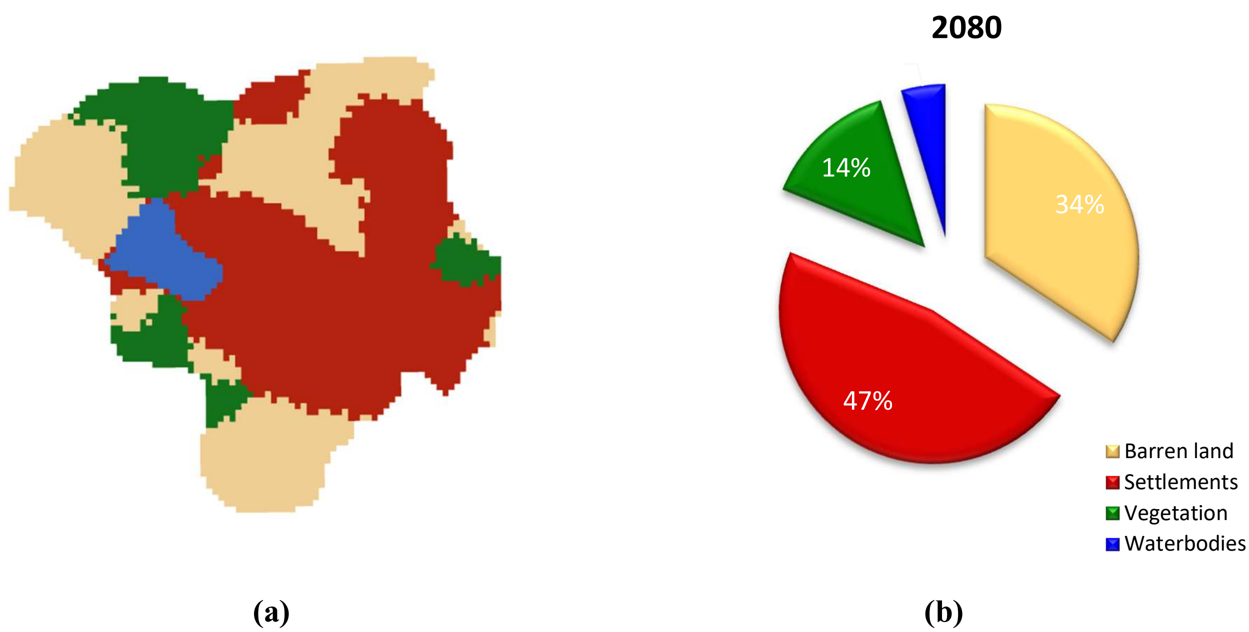
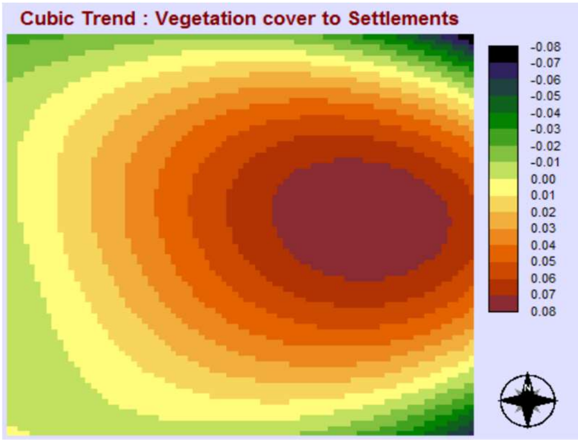
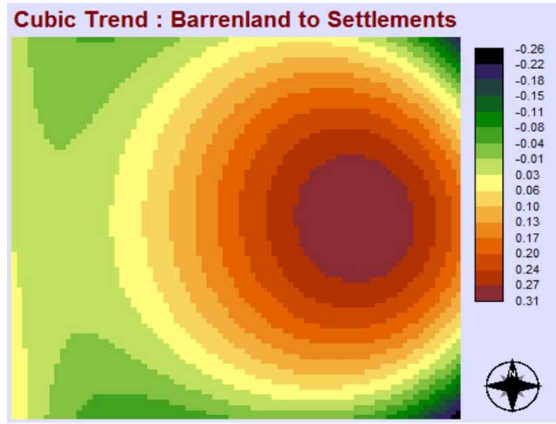


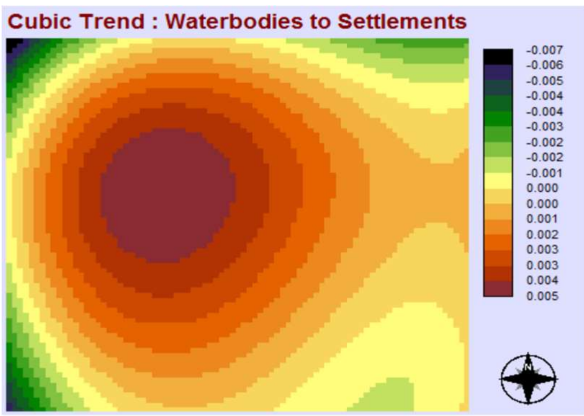
Fig. 6: (a) Predicted LULC map of Ranipet area for the year 2080 using CA-Markov (b) Percentage area changes with respect to the LULC types.



(a)



(b)



(c)

(d)

Fig. 7: Cubical trend in transformation of one LULC type to the other using IDRISI
(a) Vegetation to Settlement (b) Barren land to Settlement
(c) Water bodies to settlement (d) All the classes to settlement.

the one close to zero represents the reduction of one class to the other. Fig. 8 describes the spatial distribution of the gains and losses between the years 1997 to 2080 for each land use class. In this study area, the persistence of the existing land use is included for a better understanding of the gains and losses. It is evident from Fig. 8 (a) that the area in and around the existing settlement increases in the predicted spatial map of 2080. Since temperature and annual rainfall are not been considered in this analysis, which influences the area changes in water bodies, there could not be any significant changes observed in Fig. 8 (c).

CONCLUSION

Using land use maps for the years 1997, 2009, and 2019, the future LULC maps were predicted by the CA-Markov model and the CA-ANN technique using two different platforms efficaciously. Although these models are commonly used in predicting the future LULC transformations for a bigger area, this study successfully employed the models in a smaller area and attained satisfactory kappa indices. The rapid shift in industrialization indicated the economic development of the Ranipet district, and the prediction of future 2029 maps revealed that the growth would continue in the future as well. Changes in water bodies are almost near zero, possibly due to the monsoonal variations, mean rainfall, temperature, and groundwater fluctuations in the locality. The study gives an understanding and effectiveness of the CA-Markov and CA-ANN models. But from, the results show that the CA-Markov model predicts the future LULC change easily and more accurately than the CA-ANN model.

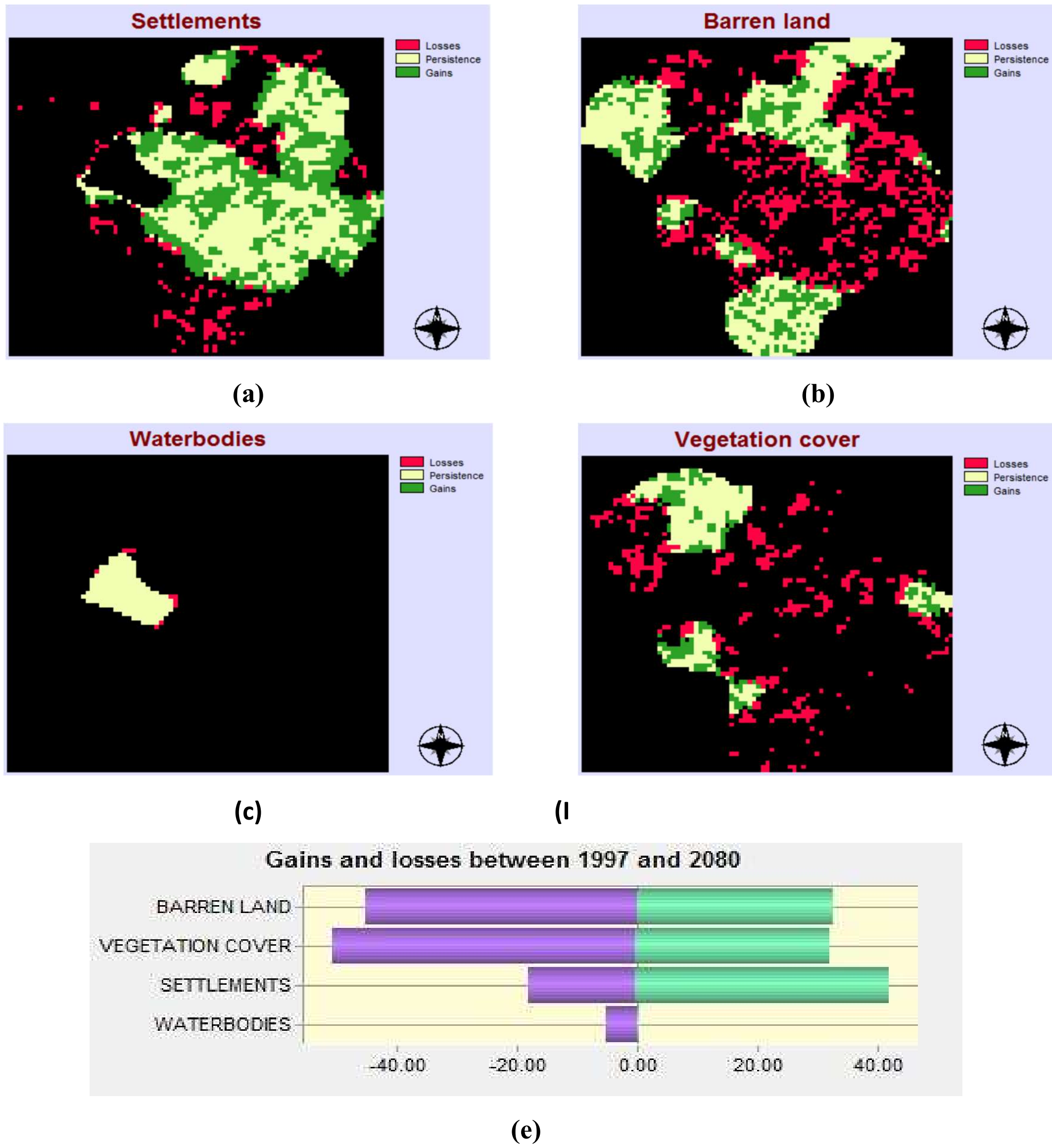


Fig. 8: Spatial distribution of gains and losses in each LULC classification type using IDRISI (a) settlement (b) barren land (c) water bodies (d) vegetation (e) percent change.

Furthermore, Land Change Modeler (LCM) in the IDRISI interface shows a widespread application in addressing the spatial and temporal dynamics and imparts knowledge about the parameters and drivers influencing land dynamics. Though the results derived have promoted the 'district's economy, the most important human demands in such areas should also be prioritized for agricultural development and the protection of the ecosystems and environment. Raising the standard of living and safeguarding the existing ecosystems are a mandate, according to 'India's statutory domestic Environmental laws. A strong, striking balance and harmony should be maintained between the imperatives of development and ecology. The Vellore case illustrates the Supreme Court's activist approach towards the implementation of 'Precaution' and 'Polluter pays,' which does little to end the prevailing problems of environmental degradation (Gupta 2018). Likewise, due consideration should be given to the land's sensitivity toward the topography and economic variables. The study also points out that land degradation cannot be addressed only by Land Use Land Cover Change maps, but it is one of the effective tools for managing and regulating land use policies in the future.

A long-term evaluation and analysis should be conducted for detailed and accurate future planning. Furthermore, it would be beneficial to the stakeholders in the decision-making process. Moreover, CA-ANN and CA-Markov models were extremely advantageous in predicting future land use changes, which would assist in a comprehensive study of land use management and planning.

ACKNOWLEDGEMENTS

This research was funded by the Science and Engineering Research Board (SERB, grant number EMR/2016/006662), Department of Science and Technology (DST), India. The authors also extend their thanks to the Centre for Disaster Mitigation and Management (CDMM), VIT Vellore, and the School of Civil Engineering (SCE), VIT Vellore, for the valuable support and for providing the research environment.

REFERENCES

Ahmed, B. and Ahmed, R. 2012. Modeling urban land cover growth dynamics using multi-temporal satellite images: A case study of Dhaka, Bangladesh. ISPRS Int. J. Geo-Inform., 1: 3-31.

Al-Sharif, A.A. and Pradhan, B. 2014. Monitoring and predicting land use change in Tripolimetropolitan city using an integrated Markov chain and cellular automata models in GIS. Arab. J. Geosci., 7: 4291-4301.

Arsanjani, J.J., Kainz, W. and Mousivand, A.J. 2011. Tracking dynamic land-use change using spatially explicit Markov Chain based on cellular automata: The case of Tehran. Int. J. Image Data Fusion, 2(4): 329-345.

Arsanjani, J.J. 2012. Dynamic Land Use/Cover Change Simulation: Geosimulation and Multi Agent Based Modelling. Springer-Verlag, Berlin Heidelberg.

Arsanjani, J.J., Helbich, M., Kainz, W. and Boloorani, A.D. 2013. Integration of logistic regression, Markov chain and cellular automata models to simulate urban expansion. Int. J. Appl. Earth Observ. Geoinform., 21: 265-275.

Araya, Y.H. and Cabral, P. 2010. Analysis and modeling of urban land cover change in Setúbal and Sesimbra, Portugal. Remote Sensing., 2: 1549-1563.

Balzter, H. 2000. Markov chain models for vegetation dynamics. Ecol. Model., 126: 139-154.

Batty, M. and Xie, Y. 1994. Modeling inside GIS: Part 1. Model structures, exploratory spatial data analysis, and aggregation. Int. J. Geogr. Inform. Sys., 8(3): 291-307.

Berberoğlu,, S., Akın, A. and Clarke, K.C. 2016. Cellular automata modeling approaches to forecast urban growth for Adana, Turkey: A comparative approach. Landsc. Urban Plan., 153: 11-27.

Brown, D.G., Pijanowski, B.C. and Duh, J.D. 2000. Modeling the relationship between land use and land cover on private lands in the Upper Midwest, USA. J. Environ. Manag., 59: 247-263.

Bucx, T., Marchand, M., Makaske, B. and van de Guchte, C. (Eds.) 2010. Comparative assessment of the vulnerability and resilience of 10 deltas, synthesis report. Delta Alliance Report; No. nr. 1, Deltares. https://edepot.wur.nl/188269

Butchart, S.H.M., Walpole, M., Collen, B., Van Strien, A., Scharlemann, J.P.M., Almond, R.E.A and. Oldfield, T.E.E. 2010. Global biodiversity: Indicators of recent declines. Science, 328: 1164-1168.

Cabral, A.I.R., Vasconcelos, M.J., Oom, D. and Sardinha, R. 2010. Spatial dynamics and quantification of deforestation in the central-plateau woodlands of Angola (1990-2009). Appl. Geogr., 31: 1185-1193.

Couclelis, H. 1985. Cellular worlds: a framework for modeling micro-macrodynamics. Environ. Plan., 17(5): 585-596.

Gantumur, B., Wu, F., Vandansambuu, B., Tsegmid, B., Dalaibaatar, E. and Zhao, Y. Spatiotemporal dynamics of urban expansion and its simulation using CA-ANN model in Ulaanbaatar, Mongolia. Geocarto Int., 17: 237. DOI: 10.1080/10106049.2020.1723714.

Geist, H.J. and Lambin, E.F. 2004. Dynamic causal patterns of desertification. Bioscience, 54: 817-829.

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

Jat, M.K., Choudhary, M. and Saxena, A. 2017. Application of geo-spatial techniques and cellular automata for modelling urban growth of a heterogeneous urban fringe. Egypt. J. Remote Sens. Space Sci., 20(2): 223-241.

Kaliraj, S., Chandrasekar, N., Ramachandran, K.K., Srinivas, Y. and Saravanan, S. 2017. Coastal land use and land cover change and transformations of Kanyakumari coast, India using remote sensing and GIS. Egypt. J. Remote Sens. Space Sci., 16: 454

Keshtkar, H. and Voigt, W. 2015. A spatiotemporal analysis of landscape change using an integrated Markov chain and cellular automata models. Model Earth Syst. Environ., 2(1): 10.

Koomen, E. Borsboom-van Beurden, J. 2011. Land-use Modelling in Planning Practice. Springer, XVI-214.

Lambin, E.F. Turner, B.L. Geist, H.J. Agbola, S.B. Angelsen, A. Bruce, J.W. Coomes, O.T. Dirzo, R. Fischer, G. Folke, C. George, P.S. Homewood, K. Imbernon, J. Leemans, R. Li, XB. Moran, EF. Mortimore, M. Ramakrishnan, P.S. Richards, JF. Skanes, H. Steffen, W. Stone, GD. Svedin, U. Veldkamp, TA. Vogel, C. Xu, JC. 2001. The causes of land-use and land-cover change: moving beyond the myths. Global Environmental Change: Human and Policy Dimensions,11: 261–269.

Lambin, E.F. 1997. Modeling and monitoring land-cover change processes in tropical regions. Progress in Physical Geography, 21: 375-383.

Li, T. and Li, W. 2015. Multiple land use change simulation with Monte Carlo approach and CA-ANN model, a case study in Shenzhen, China. Environmental Systems Research, 4(1).

Li, S.H., Jin, B.X., Wei, X.Y., Jiang, Y.Y. and Wang, J.L. 2015. Using CA-Markov model to model the spatiotemporal change of land use/cover in Fuxian lake for decision support. ISPRS Annals Photogram. Remote Sens. Spatial Inform. Sci., 42: 163-168.

Maithani, S. 2015. Neural networks-based simulation of land cover scenarios in Doon Valley, India. Geocarto Int., 30: 163-185.

Mendoza, M.E., Granados, E.L., Geneletti, D., Pérez-Salicrup, D.R. and Salinas, V. 2011. Analyzing land cover and land use change processes at watershed level: a multitemporal study in the Lake Cuitzeo Watershed, Mexico (1975-2003). Appl. Geogr., 31: 237-50.

Mishra, V.N. and Rai, P.K. 2016. A remote sensing aided multi-layer perceptron Markov chain analysis for land use and land cover change prediction in Patna district (Bihar), India. Arabian Journal of Geosciences, 9(4): 1-18.

Mondal, M.S., Sharma, N., Garg, P.K. and Kappas, M. 2016. Statistical independence test and validation of CA Markov land use land cover (LULC) prediction results. Egypt. J. Remote Sens. Space Science, 19(2): 259-272.

Mozumder, C. and Tripathi, N.K. 2014. Geospatial scenario based modelling of urban and agricultural intrusions in Ramsar wetland Deepor Beel in Northeast India using a multi-layer perceptron neural network. Int. J. Appl. Earth Observ. Geoinform., 32: 92-104.

Mustafa, A., Cools, M., Saadi, I. and Teller, J. 2017. Coupling agent-based, cellular automata and logistic regression into a hybrid urban expansion model (HUEM). Land Use Policy, 69: 529-540.

Mustafa, A. Heppenstall, A. Omrani, H. Saadi, I. Cools, M. and Teller, J. 2018. Modeling built-up expansion and densification with

multinomial logistic regression, cellular automata and genetic algorithm. Comp. Enviro. Urban Syst., 67: 147-156.
Muyibula, Z., Jianxina, X., Muhtara, P., Qingdongc, S. and Rund, Z. 2018. Spatiotemporal changes of land use/cover from 1995 to 2015 in an oasis in the middle reaches of the Keriya River, southern Tarim Basin, Northwest China. Catena, 171: 416-425.
Nong, Y. and Du, Q. 2011. Urban growth pattern modeling using logistic regression. Geo-Spatial Inform. Sci., 14(1): 62-67.
Norman, L., Feller, M. and Guertin, D.P. 2009. Forecasting urban growth across the united states–Mexico border. Comp. Environ. Urban Syst., 33: 150-159.
Pan, J.H., Su, Y.C., Huang, Y.S. and Liu, X. 2012. Land use & landscape pattern change and its driving forces in Yumen city. Geogr. Res., 31(9): 1631-1639.
Parsa, V.A., Yavari, A. and Nejadi, A. 2016. Spatio-temporal analysis of land use/land covers pattern changes in Arasbaran Biosphere Reserve: Iran. Model. Earth Syst. Environ., 2(4): 178.
Pijanowski, B.C., Brown, D.G. and Manik, G. 2002. Using neural nets and GIS to forecast land use changes: a land transformation model. Comp. Environ. Urban Sys., 26(6): 553-575.
Rahman, M.T.U., Tabassum, F., Rasheduzzaman, M., Saba, H., Sarkar, L., Ferdous, J., Uddin, SZ. and Islam, AZ. 2017. Temporal dynamics of land use/land cover change and its prediction using CA-ANN model for south western coastal Bangladesh. Environ. Monit. Assess., 56: 189: 565.
Reynolds, J.F. and Smith, S.M. 2002. Global Desertification: Do Humans Cause Deserts? Dahlem University Press, Berlin.
Rimal, B., Zhang, L.F., Keshtkar, H., Wang, N. and Lin, Y. 2017. Monitoring and modeling of spatiotemporal urban expansion and land-use/land-cover change using integrated Markov chain cellular automata model. Int. J. Geogr. Inform., 6(9): 288.
Gupta, R. 2018. Vellore Citizen's Welfare Forum v. Union of Indian and Others: A critique of Precautionary and Polluter Pays Principle.
Romm, J. 2011. Desertification: the next dust bowl. Nature, 478: 450-451.
Sang, L., Zhang, C., Yang, J., Zhu, D. and Yun, W. 2011. Simulation of land use spatial pattern of towns and villages based on CA-Markov model. Math. Comp. Model, 54: 938-943.
Saputra, M.H. and Lee, HS. 2019. Prediction of land use and land cover changes for north Sumatra, Indonesia, using an artificial-neural-network-based cellular automaton. Sustainability, 11: 3024.
Schröter, D., Cramer, W. and Leemans, R. 2010. Ecosystem service supply and vulnerability to global change in Europe. Science, 310: 1333-1337.
Sellers, P.J., Meeson, B.W., Hall, F.G., Asrar, G., Murphy, R.E., Schiffer, R.A., Bretherton, F.P., Dickinson, R.E., Ellingson, R.G., Field, C.B., Huemmric, K.F., Justice, C.O., Melack, J.M., Roulet, N.T., Schime, D.S. and Try, P.D. 1995. Remote sensing of the land surface for studies of global change: models, algorithms and experiments. Remote Sens. Environ., 51(1): 3-26.
Singh, S.K., Srivastava, P.K., Gupta, M., Thakur, J.K. and Mukherjee, S. 2014. Appraisal of land use/land cover of mangrove forest ecosystem using support vector machine. Environm. Earth Sci., 71: 2245-2255.
Srinivasa Gowd, S. and Govil, P.K. 2008. Distribution of heavy metals in surface water of Ranipet industrial area in Tamil Nadu, India. Environ. Monit. Assess., 136: 197-207.
Subedi, P., Subedi, K. and Thapa, B. 2013. Application of a hybrid cellular automaton Markov (CA-Markov) Model in land-use change prediction: a case study of saddle creek drainage Basin, Florida. Appl. Ecol. Environ. Sci., 1(6): 126-132.
Sutton, P.C., Anderson, S.J., Costanza, R. and Kubiszewski, T. 2016. The ecological economics of land degradation: Impacts on ecosystem service values. Ecol. Econ., 129: 182-192.
Tamil Nadu Pollution Control Board (TNPCB) 2010. Revised Action Plan for critically polluted Area – Ranipet, 2010. https://www.tnpcb.gov.in/pdf/Action_plan_Ranipet070916.pdf
Tripathy, P. and Kumar, A. 2019. Monitoring and modelling spatio-temporal urban growth of Delhi using cellular automata and geoinformatics. Cities, 90, 52-63.
Triantakonstantis, D. and Mountrakis, G. 2012. Urban growth prediction: A review of computational models and human perceptions. J. Geogr. Inform. Syst., 4: 555-587.
Turner, B.L., Lambin, E.F. and Reenberg, A. 2007. The emergence of land change science for global environmental change and sustainability. Proceed. Nat. Acad. Sci., 104(52): 20666-20671.
Vasconcelos, M.J., Cabral, A.I.R., Melo, J.B., Pearson, T.R.H., Pereira, H.A. and Cassam, V. 2015. Can blue carbon contribute to clean development in West Africa? The case of Guine-Bissau. Mitig. Adap. Strat. Glob. Change, 20: 1361-1383.
Verburg, P.H., Eck, J.R.V., Hijs, T.C.D. and Dijst, M.J.S. 2004. Determination of land use change patterns in the Netherlands. Environ. Plan. B Urban Anal. City Sci., 31(1): 125-150.
Wang, J. and Maduako, I.N. 2018. Spatio-temporal urban growth dynamics of Lagos Metropolitan Region of Nigeria based on Hybrid methods for LULC modeling and prediction. Europ. J. Remote Sens., 51: 251-265.
White, R. and Engelen, G. 1994. Cellular dynamics and GIS: Modeling spatial complexity. Geogr. Sys., 1(3): 237-253.