URBAN GROWTH PREDICTION USING GEOSIMULATION AND MODELING

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URBAN GROWTH PREDICTION USING GEO-SIMULATION AND MODELING

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KEYWORDS: Urban growth, Geo-simulation, Remote sensing, Land use land cover, Transition potential, Land change prediction.

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ABSTRACT

This paper deals with application of geo-simulation and modelling techniques for the prediction of future urban growth pattern in the year 2045, for the new capital region of Andhra Pradesh, India. For this, remote sensing satellite images of the years 1995, 2005 and 2015 were processed in ERDAS to produce land use land cover (LULC) images. From the changes between these images, transition potential models were created in TERRSET to run the land change prediction model. From the LULC images of 1995 and 2005, image for 2015 was predicted, which is compared with already developed one, for validation. The accuracy of prediction is more than 80%. Now LULC of 2025 was predicted using the combination of 2005 and 2015, and that of 2045 was predicted using the combination of 2005 and 2025. The change detection was also presented. The predicted image will help urban planners for better environmental management.

I. INTRODUCTION

In the new global economy, the rapid urban growth and its environmental management have become a central issue for the policy makers. Keeping sustainability into account, the environmental implications of the unplanned urban sprawl shall be eliminated to the possible extent. For this prediction of extent of urban growth for future in the form of maps will be of immense use in the decision making for the urban planners. Urbanization being a dynamic process involves the expansion of urban pockets in response to the population growth, industrialization, political, cultural and several other socio-economic factors. This brings a lot of change in the biophysical characteristics of the land surface of the urban areas. Accelerated urbanization also creates several challenges, including solid waste disposal problem, water shortage, air pollution, reductions in green space and associated environmental issues. Specific problems associated with unplanned rapid urbanization include large-scale land cover changes, disturbance in ecological diversity, degradation to the environment, consumption of resources, development of urban heat islands, changes in local or micro climate, soil erosion, changes in hydrological cycle impairing surface water and ground water regime and so on. This eventually leads to unsustainable growth and over a period of time, urban dwelling may become a miserable one in the future.

To address these issues, and to mitigate the adverse effects of urban sprawl, observation of current trends of urban growth, identification of vulnerable things due to the present condition, prediction of future expansion and its scope, and planning for combating the future potential threats must be adopted. In this connection, this paper explores the application of geo- simulation techniques to predict the future urban expansion. Several researchers contributed a considerable amount of works in this direction and extensively documented. In fact, the application of geo-simulation for prediction of urban growth has been observed to be evolving with new modifications and updates incorporating the latest computer-assisted modelling and simulation techniques.

Urban growth and sprawl is a complicated process that is determined by the interactions of biophysical factors, human factors and sociological factors in space and time on different levels. (Barredo, Kasanko, McCormick, & Lavalle, 2003; Lambin & Geist, 2001). Modeling is an excellent and valuable way to understand a process (Costanza & Ruth, 1998) where one can have a scope for verification of what-if conditions. There still lacks spatially explicit urban expansion models that can effectively trace the urban development in the past and predict possible expansion scenarios in the future so that the related urban planning policies can be examined. However, the geo-simulation techniques demonstrated in this paper are most promising and yields reasonable results.

Since the available land use models are useful tools to understand the land use processes and patterns, and support land-use planning and policy making (Verburg, Veldkamp, deKoning, Kok, & Bouma, 1999), further development of the urban land change model to effectively describe the complicated process of urban expansion, which can predict the future expansion is still indispensable (Chen, Gong, He, Luo, & Tamural, 2002).

Though there are a variety of approaches that have been used to model the spatial process of urban growth, including potential models (Weber & Puissant, 2003), Markov chains (Lo´ pez, Bocco, Mendoza, & Duhau, 2001) and spatial logistic regression, Cellular Automata (CA) based Markov chain models provide a more realistic image out puts. Cheng & Masser have provided a review of models developed for urban dynamics during the last half century(Cheng & Masser, 2003).

Recently, there has grown literature on the applications of cellular automata (CA) based models in urban growth and land-use change (Batty, Couclelis, & Eichen, 1997; Clarke, Hoppen, & Gaydos, 1997; White & Engelen, 1997; Wu & Webster, 1998). A CA model is a dynamic model with surrounding interactions to reflect the evolution within the system, where space and time are considered as discrete units and space is often represented as a regular lattice of two dimensions (White & Engelen, 1997). CA-based models are well known to have the strong ability to represent non-linear, spatial and stochastic processes. Several research works have already demonstrated the CA model's capability to simulate spatial pattern and process of urban expansion and sprawl in a very realistic way.

CA cannot represent well macro-scale political, economic and cultural driving forces that influence urban expansion (Ward, Murray, & Phinn, 2000). Research is urgently needed on how to improve a CA model's ability to represent the complexity of urban expansion influenced by human and natural factors at different scales. CA based Markov chain modelling incorporating artificial neural work for optimization of the transition potential is found to be very effective. The CA-based hybrid models improve the CA's ability to reflect actual land-use change and have drawn great interests in the research community.

The objective of the present work is to demonstrate the application of geo-simulation techniques to predict the future urban expansion. For this CA and Markov based model is used to predict LULC of year 2025 and 2045 from the LULC of the year's 1995, 2005 and 2015. Model performance and efficiency were discussed.

II. Study Area and Data

2.1 Study Area:

The historical city, Vijayawada, situated at the geographical centre of Andhra Pradesh state in India, on the banks of Krishna River with latitude $16^{0}31^{1}$ N and longitude 80^{0} 39^{1} E, now has become the capital of the new state called Andhra Pradesh. The capital region comprises two big cities viz., Vijayawada and Guntur. There is a tremendous scope for urban development because of the new state capital construction and there will be severe alterations in the landscape of the area. For present study, a rectangular area which includes the capital region has been selected.

2.2 Data Collection:

Toposheets: For the present work Toposheets of 1:50,000 scale for the corresponding region with No 65D/6, 65D/7, 65D/8, 65D/9, 65D/10, 65D/11, 65D/14, 65D/15 are collected from Survey of India. These are processed, and study area was obtained by mosaic of the toposheets. The elevation map of the study area which was cut from the SRTM image, down loaded from '**www.earthexplorer.usgs.gov**' was used for this work.

Satellite images: Landsat satellite images which were downloaded from the USGS earth explorer website:
'**www.earthexplorer.usgs.gov**' are used in this work. The details of the Landsat satellite images selected for the present work are given in the Table.1 below.

Table.1 below. Table.1 Details of Landsat satellite imagery downloaded.

S.NO	DATE	RESOLUTION	BANDS	LANDSAT series	PATH/ROW	RGB	SENSOR
1	17-12-1995	30	7	5	142/49	1 2 3	TM
2	11-05-2005	30	7	5	142,49	1 2 3	TM
3	23-05-2015	30	11	8	142,49	2 3 4	OLI/TIRS

Field Survey Data: Field's survey has been conducted to assist the classification of the satellite images into different land use land cover types. For this nearly 100, points were selected in the satellite image of the entire study area which are unidentified land use land cover types or ambiguous about classification. The land-cover type within the area was noted by visiting the site, and photographs were taken for reference. This data is very useful to identify different features observed in satellite images for classification and also for the accuracy assessment of classification. For collection of field data at 100 points, corresponding coordinates were placed on Google Earth image and using GPS and compass the points were located on the ground during the field visit to collect the data.

III. Methodology

The present study involves processing of the Landsat satellite images, development of LULC images and application of Land change modeller. After pre-processing the satellite images, supervised classification with the maximum likelihood algorithms is used to produce LULC images using ERDAS imagine. Six land use land cover classes were considered viz., Built-up, Open land, Light Vegetation, Dense Vegetation, Water and Sand. Field data photographs are studied and used for accurate signature development. River course is shown separately as a single class since it includes some water, sand and grass. The produced land use land cover images are analysed, and change detection was carried out. The output LULC images are used to predict the future LULC image by Land Change Modeler of a geospatial analysis and modelling software TerrSet.

A Road network map is developed from Toposheets and Google earth map in ARC GIS, and fed to the Land Change Modeler (LCM). Digital Elevation map was downloaded from SRTM Data from USGS Earth explorer and used in the Land Change Modeler. By running the Land Change Modeler, after giving inputs at successive stages the predicted LULC image was obtained. Using LULC of 1995 and 2005, with 10-year span, LCM was run to predict LULC of 2015. This LULC of 2015 is compared with the already developed LULC 0f 2015 by ERDAS for accuracy assessment and found to be with good agreement. Now using LULC of 2005 and 2025, with 20 years span, the future LULC of 2045 was predicted by LCM. The methodology adopted in this work was shown in the Figure 1.

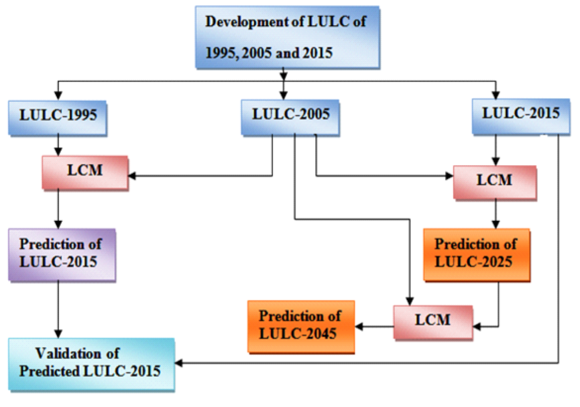

Figure 1.Methodology adopted in this work

IV. RESULTS AND DISCUSSION

In this section, the output images of LULC and analysis were presented. First, the pre-processed satellite images of the study area are given in Figure 2. The LULC images produced from Landsat satellite images for the years 1995, 2005 and 2015 using image-processing software ERDAS imagine are given in the Figure 3. For developing LULC images supervised classification technique was adopted with maximum likely hood algorithm. Seven types of LULC classes were observed in the study area and hence seven LULC classes were developed. While developing the LULC images, field data was used to calculate the classification accuracy, which was found to be nearly 80%

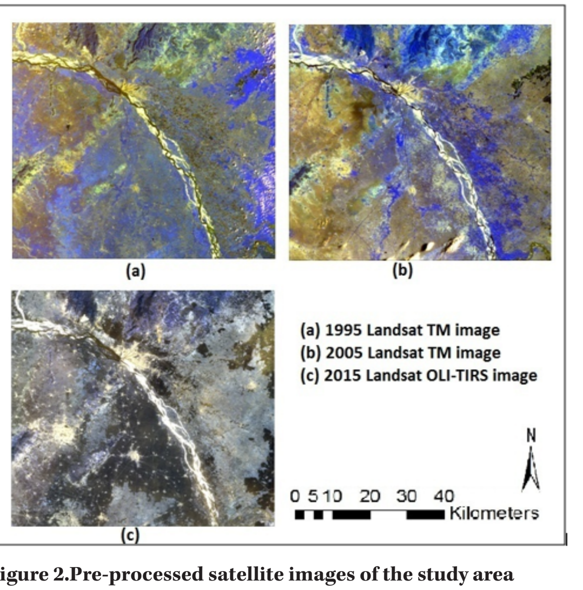

Figure 2.Pre-processed satellite images of the study area

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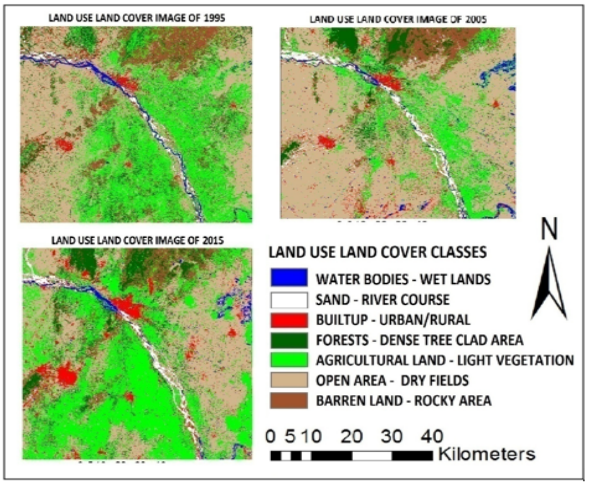

Figure 3.LULC images of 1995, 2005 and 2015 developed from satellite images

In this work, LCM was applied in three stages. Using Landsat images of 1995 and 2005, LULC image of 2015 was predicted first and compared with actual LULC image developed using Landsat image of 2015. A good accuracy was obtained for the validation. Now using 2005 and 2015 images, LULC images of 2025 &2045 were predicted. The change detection analysis was carried and presented. The screen shot image of Land Change Modeler was shown in the following Figure.4. In the second stage, using LULC images of 2005 and 2015, LULC image of 2025 was predicted. The gains and losses in each LULC class between 2005 and 2015, along with net change between 2005 and 2015 were shown in the Figure 5.

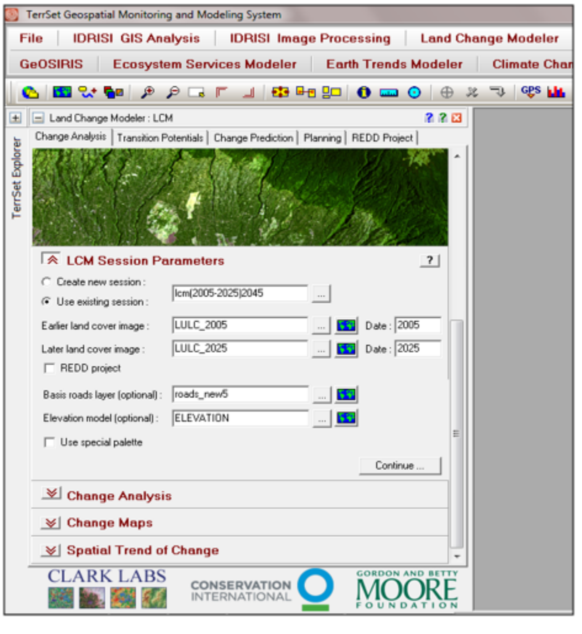

Figure 4.Land Change Modeler taking LULC of 2005 and 2025 to predict LULC of 2045

As we are mainly interested in the urban growth, only contributions to the net change in the built-up area were considered and shown. Similarly in the third stage of LCM application, using LULC images of 2005 and 2025, LULC image of 2045 was predicted. The gains and losses in each LULC class between 2005 and 2025, along with net change between 2005 and 2025 were shown in the Figure 6. Also contributions to the net change in the built-up area are shown.

The output LULC images, predicted from Land Change Modeler for the years 2025, and 2045 were shown in the following Figures 7 & 8.

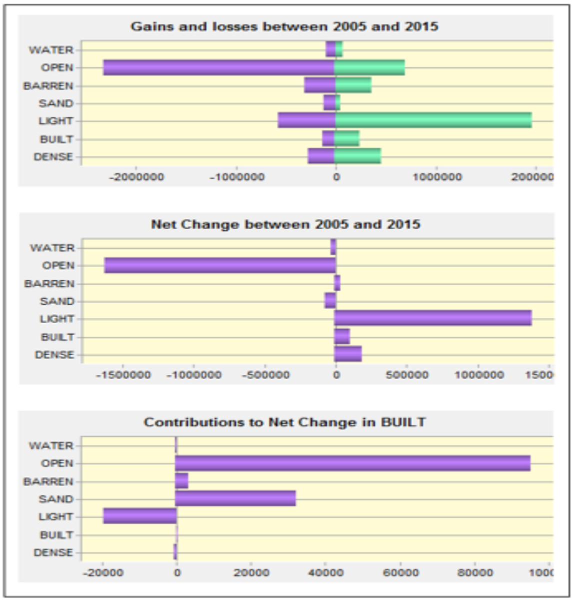

Figure 5. Gains, Losses and Net change in LULC classes between 2005 and 2015

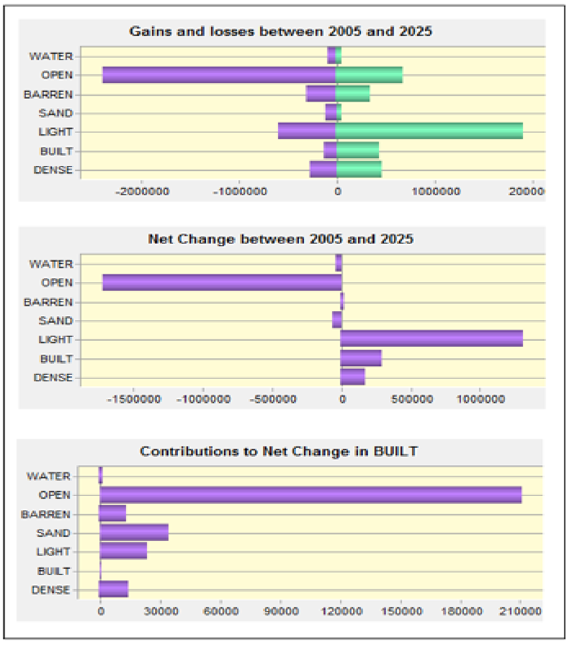

Figure 6. Gains, Losses and Net change in LULC classes between 2005 and 2025

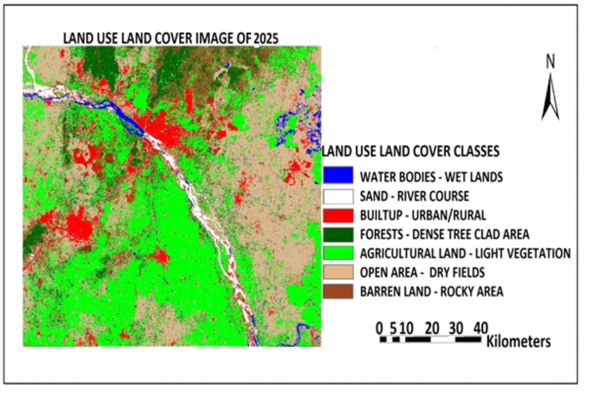

Figure 7. The Predicted LULC image of the year 2025

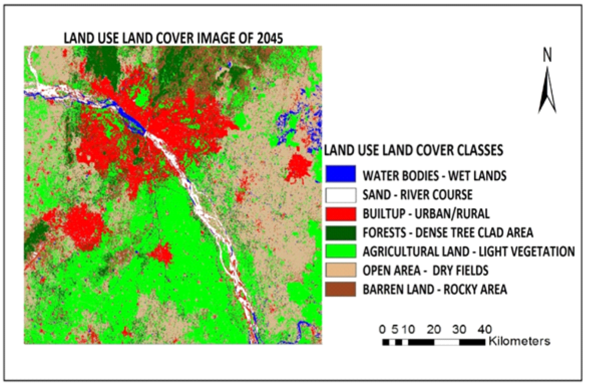

Figure 8. The Predicted LULC image of the year 2045

From the Figure 5, by observing the gains and losses between 2005 and 2015 it was clearly understood that there is a significant decrease in the 'open' area and increase in 'light 'vegetation' area. This is because of conversion of agricultural areas and other light vegetation areas into the open area first and subsequently into the built-up area. In this process, open area is directly converted into the built-up area. This can be observed on the graph showing the contributions to net change in the built-up area. Also there is a contribution from sandy area to the built-up area; this is because of encroachment on the river side area and development of small residential areas along the river side. However, these constructions are not concrete based, but roof tops are made up of cement-fibre sheets. Hence they were shown to contribute to the built-up area. After conversion, some built-up area may appear to be like light vegetation area because of development of greenery in the form of parks and others, hence there is negative contribution to the built-up area from light vegetation area as shown in the graph.

Table.2 Change detection and analysis between 1995 and 2015

LAND USE TYPE	1995	%	2015	%	DIFF(%)	1995-2015	%
WATER BODIES	9187.83	1.52	12601.8	2.09	0.57	3413.97	37.16
SAND	7842.24	1.30	11156.5	1.85	0.55	3314.26	42.26
BUILT UP	16391.63	2.72	39543.3	6.55	3.84	23151.67	141.24
FOREST	62305.8	10.32	86194.4	14.28	3.96	23888.6	38.34
AGRICULTURE	296007	49.05	21274.5	3.53	-45.52	-274732.5	-92.81
OPEN-DRY	137502	22.78	391461	64.86	42.08	253959	184.69
BARREN - ROCKY	74285.5	12.31	41290.5	6.84	-5.47	-32995	-44.42
TOTAL	603522	100	603522	100	0	0	-

Table. 3 Change detection and analysis between 2015 and 2025

LAND USE TYPE	2015	%	2025	%	DIFF (%)	2015-2025	%
WATER BODIES	12601.8	2.09	10939.86	1.81	-0.28	-1661.94	-13.19
SAND	11156.5	1.85	13330.08	2.21	0.36	2173.58	19.48
BUILT UP	39543.3	6.55	49479.3	8.20	1.65	9936	25.13
FOREST	86194.4	14.28	59415.7	9.84	-4.44	-26778.7	-31.07
AGRICULTURE	21274.5	3.53	205866.33	34.11	30.59	184591.83	867.67
OPEN-DRY	391461	64.86	51479.1	8.53	-56.33	-339981.9	-86.85
BARREN - ROCKY	41290.5	6.84	213011.63	35.29	28.45	171721.13	415.89
TOTAL	603522	100.00	603522	100.00	0.00	0	-

Table. 4 Change detection and analysis between 2015 and 2045

LAND USE TYPE	2015	%	2045	%	DIFF (%)	2015-2045	%
WATER BODIES	12601.8	2.09	10311.03	1.71	-0.38	-2290.77	-18.18
SAND	11156.5	1.85	13958.31	2.31	0.46	2801.81	25.11
BUILT UP	39543.3	6.55	83453.22	13.83	7.28	43909.92	111.04
FOREST	86194.4	14.28	56366.65	9.34	-4.94	-29827.75	-34.61
AGRICULTURE	21274.5	3.53	191007.54	31.65	28.12	169733.04	797.82
OPEN-DRY	391461	64.86	49623.95	8.22	-56.64	-341837.05	-87.32
BARREN -	41290.5	6.84	198801.3	32.94	26.10	157510.8	381.47
TOTAL	603522	100.00	603522	100.00	0.00	0	-

Similarly from the Figure 6, by observing the gains and losses between 2005 and 2025 it can be understood that there is a significant decrease in the 'open' area and 'light' vegetation area and increase in 'open' area, 'light vegetation' area and 'built-up' area along with 'dense forest' area. From the graph, showing the net change between 2005 and 2025, open area is found to decrease but light vegetation area, built-up area and dense forest area are found to increase. Regarding the contributions to the net change in the built-up area, open area contributed significantly. There are contributions to the built-up area from other classes, including barren area, sandy area, light vegetation area and dense vegetation area. From these trends, the LCM predicted the LULC of 2045 with 20-year projection period. The Change detection and analysis between different years of consideration were presented in Tables 2 to 4. Areas in hectares of different LULC classes for different years are presented in the bar graph shown in Figure.9. Percentage areas of different LULC classes for different years are shown in Figure 10.

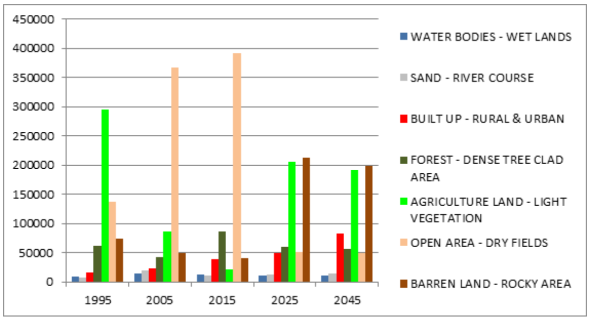

Figure 9. Areas in hectares of LULC classes for different years

Table. 5 The land areas of different classes for different years

YEAR	WATER BODIES - WET LANDS	SAND - RIVER COURSE	BUILT UP RURAL & URBAN	FOREST - DENSE TREE CLAD AREA	AGRICULTURE LAND - LIGHT VEGETATION	OPEN AREA - DRY FIELDS	BARREN LAND - ROCKY AREA
1995	9187.8	7842.2	16391.6	62305.8	296007	137502.0	74285.5
2005	14176.0	19370.4	22544.2	43171.7	87106.9	367954.7	49198.1
2015	12601.8	11156.5	39543.3	86194.4	21274.5	391461.0	41290.5
2025	10939.8	13330.1	49479.3	59415.7	205866.3	51479.1	213011.6
2045	10311.1	13958.3	83453.2	56366.6	191007.5	49623.9	198801.3

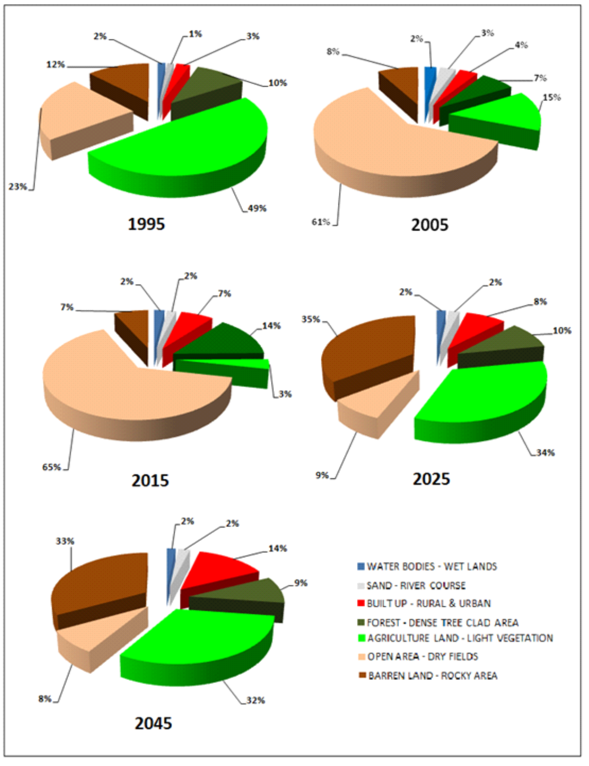

Figure 10 Percentage areas of different LULC classes for different years

Land areas of different classes for different years are shown in Table 5. Built-up area, including both rural and urban area found to be continuously increasing. The patterns of changes for different types of land use land cover classes are shown in the form of pie charts given in Figure 10. This can help for better understanding of the change detection process.

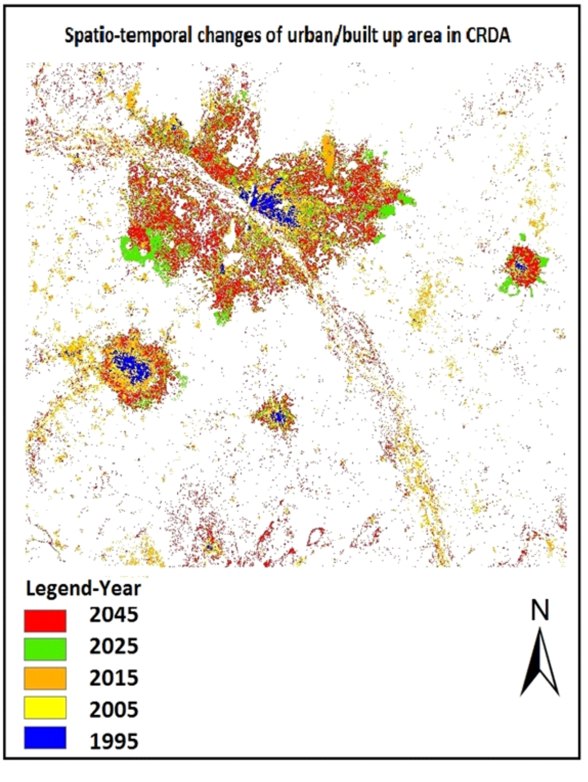

Figure 11 Growth in Built up area from 1995 to 2045

The spatio-temporal changes in built-up area, including urban as well as rural, starting from 1995 to 2015 and for projected years 2025 and 2045 is shown in the Figure 11. This Figure indicates the pattern of sprawl of built-up area, including both rural and urban from the year 1995 to 2045.

V. CONCLUSION

Geo-simulation and modelling were applied to the land use land cover images of one earlier and one later date to predict future date image. For this Land Change Modeler, an artificial neural network based image-processing software was used. New capital region of Andhra Pradesh is taken as a case study in which rapid expansion of city is expected to take place. As urban area and its expansion can be easily rather accurately studied using land use land cover images, satellite images were procured for the study area from Landsat data. These are processed to develop land use land cover images and built-up area was identified as one of the seven classes. From the land-cover images of 1995 and 2005, land cover image of 2015 was predicted. This was compared with actual land cover image of 2015, which is already developed using ERDAS to assess the predicting capability of Land Change Modeler. It was found that the model predicts well. Now using the land-cover image of 2005 and 2015, the land-cover images of 2025 and 2045 were predicted using the various other inputs, including road network, elevation data. This predicted land cover image can be used effectively for various planning activities and management of urban environmental issues.

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