International Journal of Civil Engineering and Technology (IJCIET)
Volume 9, Issue 4, April 2018, pp. 1208–1219, Article ID: IJCIET_09_04_135
Available online at http://www.iaeme.com/ijciet/issues.asp?JType=IJCIET&VType=9&IType=4
ISSN Print: 0976-6308 and ISSN Online: 0976-6316

A NOVEL APPROACH FOR PREDICTION OF FUTURE ENVIRONMENTAL IMPACTS OF URBAN GROWTH

Kusuma Sundara Kumar
Research Scholar, Department of Civil Engineering, JNT University-Kakinada, Andhra Pradesh, India

Pinnamaneni Udaya Bhaskar
Chairman, AP Public Service Commission, Prathibha Bhavan, Hyderabad, Andhra Pradesh, India

Kollipara Padma Kumari
Professor, Department of Civil Engineering, JNT University-Kakinada, Andhra Pradesh, India

ABSTRACT

This paper demonstrates a novel approach for prediction of future urban growth and its impacts using remote-sensing data, geo-simulation and soft computing techniques. Urban growth and increase of the non-pervious built-up area are the root cause of several urban environmental issues. Urban heat island, floods caused by increased runoff due to less infiltration, high-energy consumption for cooling purpose and associated emission of greenhouse gases, heat induced deaths of older people, etc. are some examples. Estimation of urban growth and its impacts can be of immense use for proper planning of mitigation measures and environmental management. Soft computing techniques like artificial neural networks (ANN) can effectively predict the nonlinear multivariate phenomenon.

The fast-growing capital region of Andhra Pradesh has been taken as the case study. Landsat satellite data for the years 1995 and 2015 of the study area were used to develop land use land cover images (LULC) and land surface temperature (LST) images by image-processing software called ERDAS. Markov chain and cellular automata based simulation techniques are applied for the 1995 and 2015 urban growth images and future urban growth images for the year 2035 have been predicted using Land Change Modeller of TERRSET.

A model using ANN has been developed in MATLAB to predict the urban microclimate (LST) images from the urban growth images. This model uses only LULC images and other ancillary data and predicts LST image without thermal bands of satellite images. The model was trained with 1995 data and tested with 2015 data with satisfactory efficiency. Hence LST image of 2035 was predicted from LULC image of 2035, which is already developed by geo-simulation. This integrated *approach can be effectively used to assess various environmental impacts that are likely to occur because of the urban growth in future and also help to decipher appropriate management plan.*

Keywords: Satellite data, Urban growth, Land change, Urban heat island, Geo-simulation, Artificial neural network.

Cite this Article: Kusuma Sundara Kumar, Pinnamaneni Udaya Bhaskar and Kollipara Padma Kumari, A Novel Approach for Prediction of Future Environmental Impacts of Urban Growth, International Journal of Civil Engineering and Technology, 9(4), 2018, pp. 1208–1219.
http://www.iaeme.com/IJCIET/issues.asp?JType=IJCIET&VType=9&IType=4

1. INTRODUCTION

Urbanization is one of the major causes for the deterioration of environmental sustainability of modern living communities. The ecological foot print, the city people bear, is increasing day by day with demographic explosion and changing lifestyles of the society. This takes its toll heavily and the depletion of natural resources, frequent occurrence of natural calamities, loss of bio diversity, are some of the well-known witnesses. In order to curb this situation the urban development must be monitored closely, and proper planning activities must be initiated keeping the ecological sustainability as the top goal. Towards this end, prediction of future growth will contribute a lot for planners and decision makers.

Urban growth and its sprawl are considered to be the chief culprits of un-sustainability developed in cities (Kennedy et al. 2011)[1]. Conversion of forests, agricultural lands and grass lands into a built-up area or constructed area is the origin for this environmental issue. Several urban environmental issues like heat islands and microclimate changes, flooding and inundation due to excess runoff, dust pollution, garbage pollution, water pollution due to sewage, noise pollution and so on occurs due to urban growth. However, all these issues are generally the outcomes of improper planning, unsustainable practices and unscientific methods adopted. Hence it is obvious that there are some precautionary measures that can be applied at the time of planning and implementing the urban expansion schemes to mitigate the above adverse effects.

Remote-sensing satellite image processing and GIS technology have been extensively used by researchers and outcomes were used by the policy makers and urban planners worldwide (Sarvestani et al. 2011; Bhatta et al. 2010) [2-3]. From satellite images, land use land cover images (LULC) of the area can be developed through which the land condition can be assessed. From LULC images, areas of the urban growth can be accurately estimated (Abubakr et al. 2014)[4]. Future LULC image prediction is an interesting research topic, and several methods were developed and commercial software packages were already available in the market (Muller & Middleton, 1994) [5]. One of the best methods which directly give the future LULC in the image format is Land Change Modeller module of TERRSET. This method works on the principles of cellular automata (CA) and Markov Chain process (Sohel & Bramle, 2015; Lauf et al. 2012) [6-7]. So using the LULC images of the past and present dates, along with other inputs like elevation road network, LULC image of the future date can be predicted(Thapa & Murayama, 2011)[8].

By using thermal bands of satellite data, land surface temperature (LST) image can be developed (Weng, 1999) [9]. With this LST image, occurrence of the urban heat island (UHI), its intensity, extent, sprawl direction can be estimated. But these thermal band data are not available with all the satellites and sometimes the data may be the unusable form due to atmospheric distortions or cloud content. Moreover, if we want to predict the future LST image, thermal band data for the future dates could not be available. Hence prediction using soft computing techniques may be the only alternative. In this direction, research has been done and a model was developed using artificial neural networks (ANN), to predict LST image from LULC image. Because LST image directly depends on the land characteristics which can be depicted by LULC image, prediction of LST from LULC is an apt option.

Most of the urban environmental problems are interlinked with urban expansion or sprawl, which increases the impervious surfaces on the ground because of the built-up area. Hence our main concern in this work is the spatial expansion of urban growth. For this urban expansion from 1995 to 2015 was studied. Future urban growth is also to be estimated or predicted in the form of image, which can be better used for understanding the direction of sprawl and other quantities like areas. With this idea, a novel approach has been proposed and demonstrated in this paper.

The main objectives of the present research are given below:

1. To develop LULC images for the years 1995 and 2015 from satellite data for the selected study area using ERDAS Imagine. 2. To predict future LULC images for the year 2035 using Land change Modeller of TERRSET. 3. To develop LST images from thermal bands of satellite data for the years 1995 and 2015 using ERDAS Imagine. 4. To develop an artificial neural network model in MATLAB for prediction of future LST image of the year 2035 from LULC of 2035. 5. Analysis of future LULC and LST images for identifying potential environmental issues.

2. STUDY AREA DATA COLLECTED

2.1. Study Area

The capital region has been delineated with approximately 8500km^2 area surrounding Amravati, the capital, for the newly formed state of Andhra Pradesh. The construction of the capital city with administrative buildings, industrial and commercial establishments, outer and inner ring road projects, water-supply projects, irrigation projects, highway projects, etc. are some of the projects, which are already initiated. The various construction activities that are taking place in this capital region consume a lot of land resources and contribute to the significant changes in the LULC and microclimate of the region. This capital region was announced in the year 2014, and since then, tremendous development has been taken place in this area at a very fast rate. There is lot of scope for development in this area and significant changes in the LULC can be clearly observed in this area, and hence it is taken as case study area. The location of the study area is shown in the following figure 1.

2.2. Data

For the present study, satellite-data were used. Satellites continuously monitor the earth and send imagery, which is useful for developing maps for environmental and land resource management. Multispectral data obtained from Landsat contain optical and thermal bands, which help us to study the land resources as well as temperature changes. This data is reasonably high resolution suitable for study of LULC and UHI. For the present research work, Landsat data for the years 1995 and 2015 were downloaded from 'earthexplorer' website: www.earthexplorer.usgs.gov.

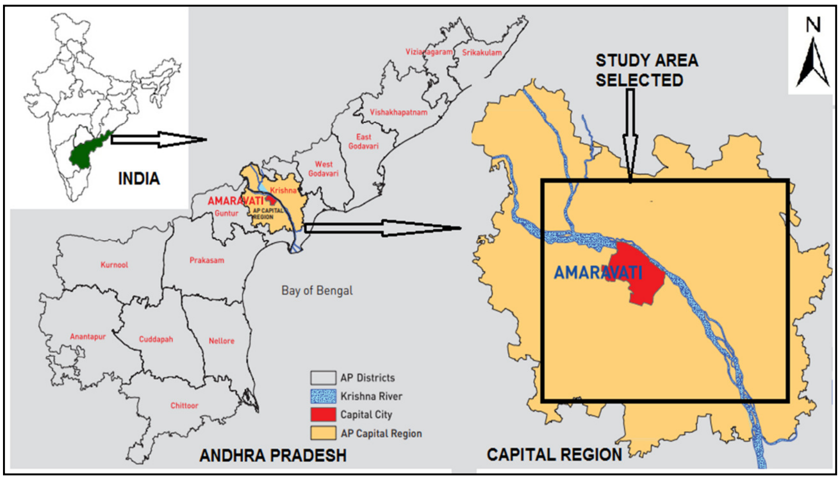
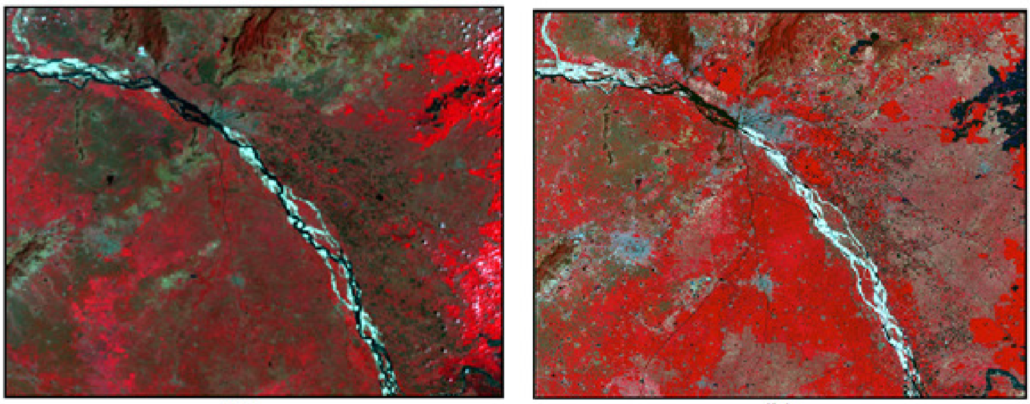


Figure 1 Location of the study area

False colour composites (FCC) of the satellite images after pre-processing and extracting study area are shown in the figures 2 (a), & (b). Elevation map was obtained from SRTM. The details of the satellite data procured were presented in the following table 1.

Table 1 Some Details of satellite data procured from Landsat

ACQUISITION DATE	SENSOR	SATELLITE	SATELLITE PASS TIME (GMT)	SWATH	REFERENCE SYSTEM	SCENE-PATH/ ROW
23-05-2015	OLI-TIRS	Landsat-8	04:56:46	170km x 185km	WRS-II	Scene-2,143/49
29-03-1995	TM	Landsat-5	04:07:22	170km x 185km	WRS-II	142/ 49



(a) (b)

Figure 2 (a) Satellite Image of 1995 as FCC, (b) Satellite Image of 2015 as FCC

3. METHODOLOGY

The present work consists of the following FIVE components parts: The entire methodology has been shown in the following figure 3 as a flow chart to understand the sequential operations. The component parts are presented below. 1. Development of land use land cover images for the years 1995 and 2015 from satellite data for the selected study area using ERDAS Imagine.

1. Development of future land use land cover images for the year 2035 using Land change Modeller of TERRSET
2. Prediction of Land surface temperature images from thermal bands of satellite data for the years 1995 and 2015 using ERDAS Imagine.
3. Prediction of future land surface temperature image of the year 2035 from land use land cover image of 2035, by developing an artificial neural network model in MATLAB.
4. Analysis of future land use land cover and land surface temperature images for identifying potential environmental issues.

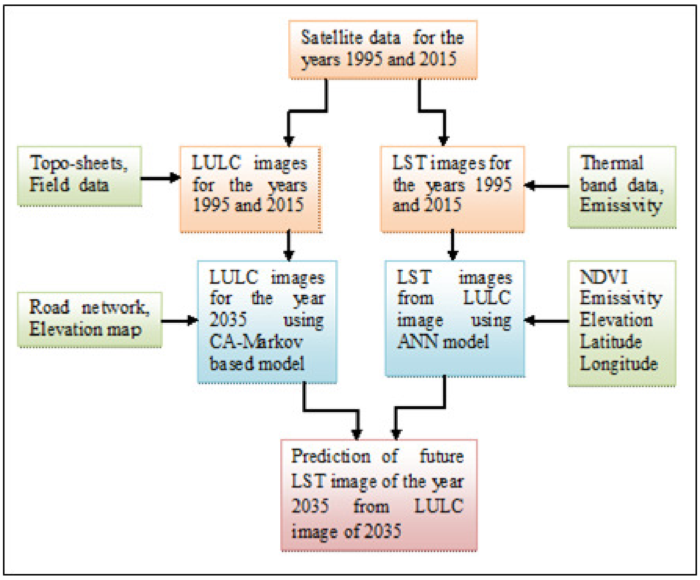


Figure 3 Flowchart showing the methodology adopted in the research work.

The above tasks were accomplished successfully and briefed in the following sections:

3.1. Land Use Land Cover images

From the satellite data R, G, B band are extracted to prepare colour composites after pre-processing. Seven typical classes of land cover were identified in the study area viz., Water bodies, Sand, Built-up, Forest, Agricultural land, Open land and Barren land. Supervised classification technique is used in ERDAS to develop LULC image. Post classification, accuracy assessment was made with incorporating field data. The classification process was repeated until sufficient accuracy was obtained. The areas of different classes were calculated for analysis and changes in these classes were estimated.

3.2. Land Surface Temperature images

Spectral radiance was first calculated for each pixel of the thermal band image using a model in ERDAS supplemented by calibration constants supplied by the Landsat data providers. From this 'at satellite brightness temperature' was derived further, which is used to estimate LST with emissivity values. The final LST image was obtained in Degrees centigrade after suitably modifying the output layer. All the calculations were done at the pixel level with the help of the model maker in ERDAS. A typical model maker was shown in the following figure 4 given below.

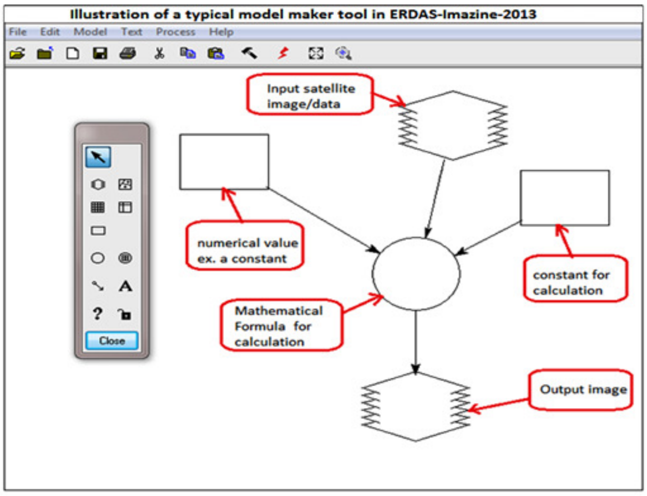


Figure 4 typical model makers in ERDAS for developing models

The procedure adopted for extracting LST image from Landsat 5, Thematic Mapper (TM) for the year 1995 was explained by the author in his research article, which was already published [10]. Similarly, the procedure adopted for extracting LST image from Landsat 8, Operation Land Imager (OLI), and Thermal Infrared Scanner (TIRS) for the year 2015 was explained by the author in a research article which was published and available in literature [11].

3.3. Prediction of LULC image of 2035

Cellular automata and Markov chain analysis based module, which is available with a geospatial modeling software called TERRSET is originally purchased from Clark Labs, USA and used in this work. This land change modeler requires past and present LULC images, elevation, road network and other probabilistic information for development of transition models, and subsequently it will produce predicted LULC image for the desired date. In this work, 1995 and 2015-year data were used as past and present scenarios and future LULC for the next 20 years that is LULC of 2035 was predicted. The Land change modeler used in the present work is shown in figure 5.

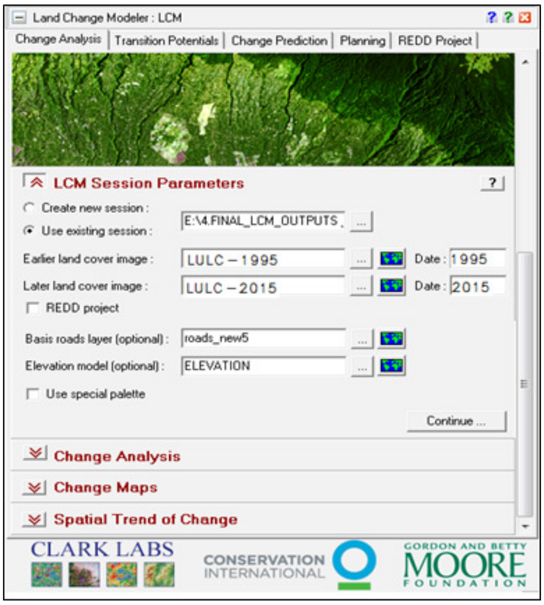


Figure 5 Land Change Modeler in TERRSET

Elevation map of the study area was extracted from SRTM image, which is a raster image. Expected road network was created as a vector shape file with available resources like the master plan for the Capital City, etc. Using all these inputs, transition potential matrices were developed from which the future LULC image of the year 2035 has been estimated. The predicted LULC image of 2035 was compared with the LULC image of 2015, and found that the prediction is the error free. This was established by the fact that the existing built-up area can never be turned into a water body or an agricultural land. However, the reverse is true. Using this concept the predicted image was thoroughly verified and validated.

3.4. Prediction of future LST image from LULC image

Future prediction of LULC is only helpful for understanding the urban growth and its sprawl, but it can't give any information regarding the thermal environment. Because estimation of thermal environmental changes requires thermal band satellite data. Hence, to overcome this lack of future thermal satellite data, prediction by artificial intelligence is preferred. In this work, an artificial neural network (ANN) model is created in MATALB, with inputs of known or available data. Feed forward back propagation algorithm is used. The network was trained with 1995 data, where both LULC and LST images are available. Again, 2015 data were used to test the network for its efficiency, after achieving sufficient efficiency LULC image of 2035 is given to the network to predict LST image of 2035. For all these operations, image data was first converted in to ASCII data in a software called Arc GIS before using in the neural network. The output of the network is again converted back to image using GIS. The detailed procedure of development of model code in MATLAB is presented in author's paper listed in reference section [12].

3.5. Analysis of future LULC and LST images for identifying potential environmental issues

Using the predicted LULC and LST images, the future urban expansion, urban heat island extent and other phenomenon were quantified and compared for change analysis from 1995 to 2015 and 2035.

4. RESULTS AND DISCUSSION

In this section, the various outputs, intermediate outcomes and final results were presented with brief description.

4.1. LULC images of 1995 and 2015

The LULC images developed from optical bands of the Landsat satellite data using supervised classification with the maximum likelihood algorithms were presented in the figure 6. Post classification, the accuracy assessment was performed with the help of field data collected from more than 100 field points visited with handheld GPS. The classification accuracy for the year 1995 was done mostly by depending on Google Earth image. The overall classification accuracy of the year 1995 was found to be 78% and the Kappa statistic as 0.68. Similarly for the year 2015, these values obtained are 93% and 0.91. The results of change detection analysis were presented in the table 2 below.

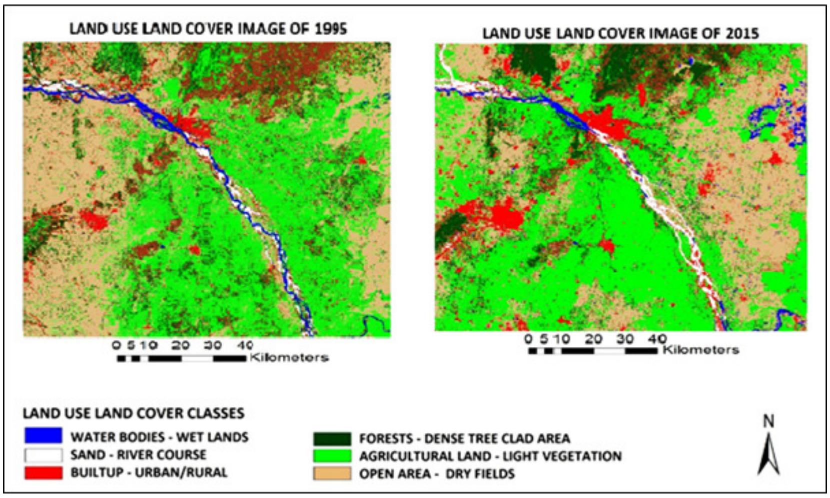


Figure 6 LULC images of the years 1995 and 2015

Table 2 Change detection analysis from 1995 and 2015

LULC-TYPE	Area in Hectares	Area in Hectares	Change in %
	1995	**2015**	**1995-2015**
WATER BODIES - WET LANDS	9187.83	12601.8	37.16
SAND - RIVER COURSE	7842.24	11156.5	42.26
BUILT UP - RURAL & URBAN	16391.63	39543.3	141.24
FOREST - DENSE TREE CLAD AREA	62305.8	86194.4	38.34
AGRICULTURE LAND - LIGHT VEGETATION	296007	21274.5	-92.81
OPEN AREA - DRY FIELDS	137502	391461	184.69
BARREN LAND - ROCKY AREA	74285.5	41290.5	-44.42
TOTAL	603522	603522	0

4.2. LST images of 1995 and 2015

The outputs obtained from the thermal image processing, LST images for the years 1995 and 2015 were given in the following figure 7.

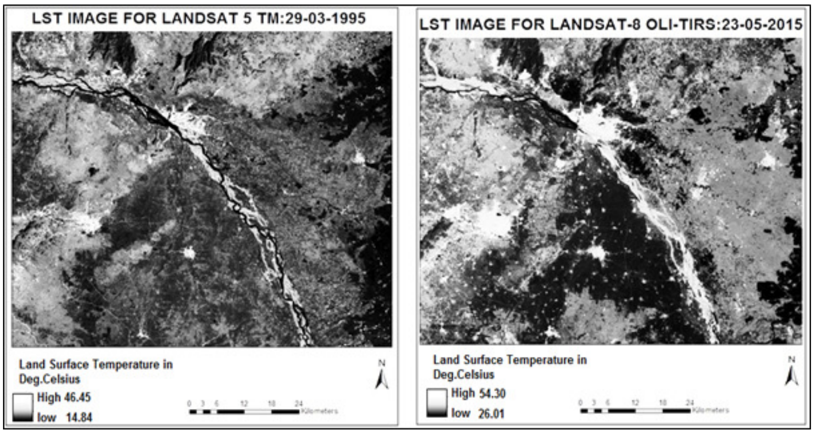


Figure 7 LST images of the years 1995 and 2015

4.3. Predicted LULC image of 2035

For the prediction of LULC image of 2035, LULC images of 1995 and 2015 were given as inputs to the Land change modeler (LCM) along with other ancillary data.

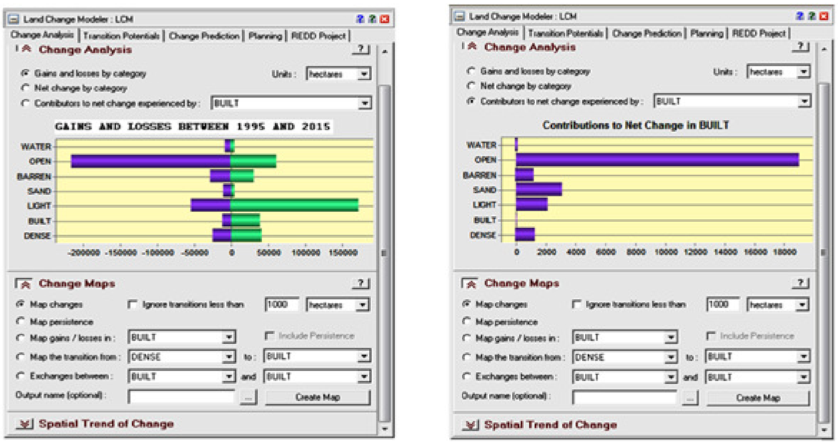


Figure 8 Gains and Losses of different LULC classes between 1995 and 2015

The LCM first estimates the gains and losses of each class of the LULC images and calculates the contributions to the net change in each class from all other classes. These are shown in figure 8. The major intermediate calculations in the LCM process are transition probability's matrices. The typical transition probability matrices were given in the following tables 3 &4.

Table 3 Transition quantified from one class to other between 1995 & 2015

Cells in :	**Expected to transition to :**						
	Class 1	**Class 2**	**Class 3**	**Class 4**	**Class 5**	**Class 6**	**Class 7**
Class 1	626085	31868	0	0	0	0	0
Class 2	0	549770	0	0	0	0	0
Class 3	0	164881	2122306	0	0	0	0
Class 4	0	0	0	148111	0	0	0
Class 5	0	22836	0	0	549155	0	0
Class 6	0	157903	0	0	0	2208904	0
Class 7	0	0	0	6987	0	0	114567

Table 4 Probability of changes from one class to other between 1995 &2015

Given :	**Probability of changing to :**						
	Class 1	**Class 2**	**Class 3**	**Class 4**	**Class 5**	**Class 6**	**Class 7**
Class 1	0.4228	0.0484	0.2393	0.0042	0.0883	0.1926	0.0045
Class 2	0.0326	0.4609	0.1836	0.0236	0.0327	0.2463	0.0202
Class 3	0.0987	0.0721	0.3785	0.0069	0.0570	0.3675	0.0193
Class 4	0.0122	0.1867	0.0603	0.4530	0.0724	0.1873	0.0283
Class 5	0.1521	0.0399	0.2474	0.0135	0.4151	0.1280	0.0039
Class 6	0.0641	0.0667	0.3914	0.0048	0.0543	0.4115	0.0071
Class 7	0.0243	0.0427	0.0784	0.0575	0.0132	0.4138	0.3701

The prediction process requires the elevation map for considering the elevation of the particular pixel; it also requires the probable road network map. The road network map will be used for calculating the distance of each pixel from the road which is very crucial for development. The cellular automata (CA) find the pattern of cells based on the constraints like elevation, distance to road, etc. The Markov chain predicts the future based on the past change. The combination of these two techniques makes it possible for prediction of future LULC image using land change modeler (LCM). The final predicted LULC image for the year 2035 was given in figure 9. The changes observed from 2015 and 2035 were also calculated for each class and presented in the table 5.

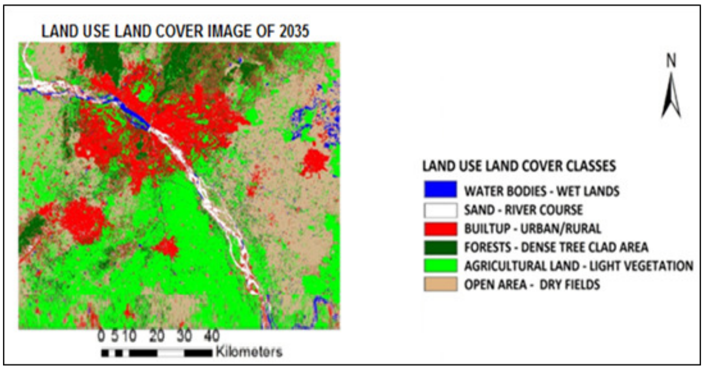


Figure 9 Predicted LULC images of the year 2035

Table 5 Change detection analysis between 2015 and 2035

LAND USE TYPE	Area in Hectares	Area in Hectares	Change in %
	2015	2035	2015-2035
WATER BODIES - WET LANDS	12601.8	10311.03	-18.18
SAND - RIVER COURSE	11156.5	13958.31	25.11
BUILT UP - RURAL & URBAN	39543.3	83453.22	111.04
FOREST - DENSE TREE CLAD AREA	86194.4	56366.65	-34.61
AGRICULTURE LAND - LIGHT VEGETATION	21274.5	191007.54	797.82
OPEN AREA - DRY FIELDS	391461	49623.95	-87.32
BARREN LAND - ROCKY AREA	41290.5	198801.3	381.47
TOTAL	603522	603522	0

4.4. Predicted future LST image from LULC image

The ANN model trained with 1995 data and tested with 2015 data yielded a predicted LST image from predicted LULC image, which is shown in the following figure 10. The prediction process involves stastical correlation between the observed and predicted values and produces a correlation coefficient along with another goodness of fit statistics. The present model after optimizing the model inputs, iterations and other parameters yielded good correlation and R^2 obtained is around 0.9. The LST image obtained from LULC image of 2035 predominantly shows the urban expansion and sprawl that are going to take place in 2035. This urban area quantification and spread direction would give the idea of the heat island.

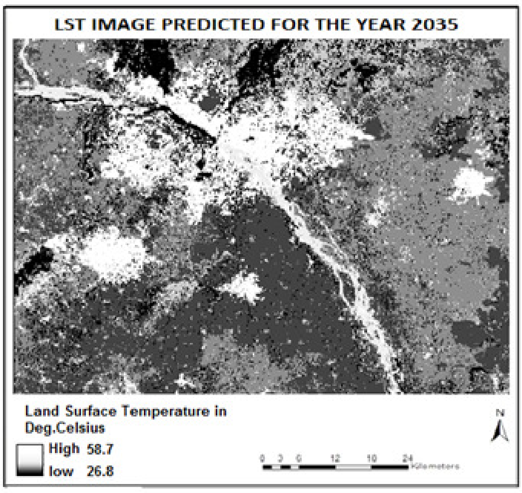


Figure 10 LST images for the year 2035

4.5. Analysis and identification of potential environmental issues

From the above table 5, it is very clearly understood that there is 111.04% growth in the built-up area which is the chief culprit of the many urban environmental issues. The infiltration capacity of the soil will be lost, and runoff quantity in rainy seasons may increase and its value may be more than double, which leads to inundation and flooding. Increase in the built-up area does not promote the decomposition of solid wastes due to lack of exposed soil and hence increase the solid waste management problems. Increase in class 5 for about 797.82% may not be the real increase in agriculture area, but it is mostly due to grass lands developed after converting agriculture land into construction sites. The LST image obtained as final output has been analysed in Arc GIS and classified into three layers, like low, medium and high according to the temperature profiles. Normally, temperature of earth above 50°C causes local air temperature of about 40°C.

Furthermore, above 40°C the comfort level of humans drastically reduces, and heat waves may create a lot of damage to civic life. Hence only area above 40°C is extracted in Arc GIS, and used for analysis. This area is corresponding to the built-up area. This can be considered as the heat island. The temporal variation of areas with more than 40° C from 1995 to 2035 was shown in the form of a graph in figure 11. From 2015 to 2035, the heat island area with temperature more than 40°C becomes double, and this may lead to heat island-related health issues.

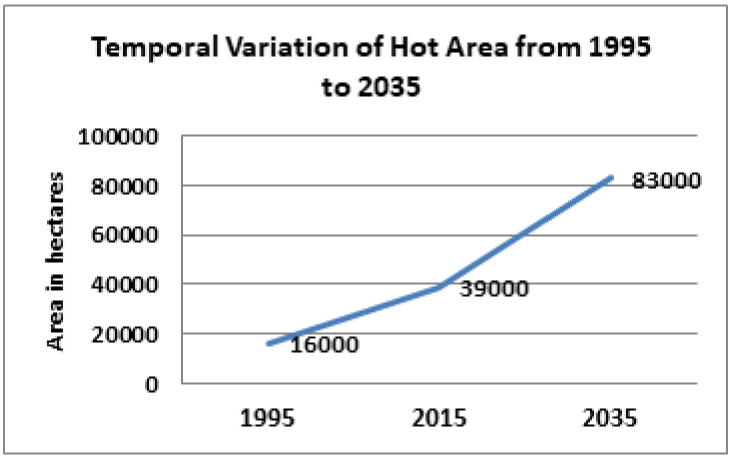


Figure 11 Temporal variation of high temperature areas(>40°C) from 1995 to 2035

5. CONCLUSIONS

Capital region of Andhra Pradesh has been taken as case study area and with the help of satellite images, Google's earth and field data, LULC images of the years 1995 and 2015 were developed with accuracy of 78&93%. By using thermal bands of satellite data, LST images of 1995 and 2015 were derived. Using land change modeler(LCM), future LULC of 2035 has been developed with the cellular automata and M chain based geo-simulation process. An ANN based model with LM-feed forward back propagation algorithm, has been developed in such a way that it can predict the LST image from future LULC image of 2035. By analyzing these LULC & LST image of 2035, urban or built-up area expansion was estimated. Intensity and extent of the urban heat island were estimated. Relevant environmental issues were highlighted. From 2015 to 2035, the urban heat island intensity will extend into two folds. The runoff and associated flooding problems will also get doubled if suitable precautionary measures were not initiated. This novel approach can be effectively used to predict future environmental issues of any desired date for adequate planning and maintaining the required mitigation measures for protecting the urban environment.

REFERENCES

[1] C. Kennedy, S. Pincetl, P. Bunje. (2011). the study of urban metabolism and its applications to urban planning and design. *Environmental Pollution,* 159, 1965-1973.

[2] Mahdi Sabet Sarvestani, Ab. Latif Ibrahim, Pavlos Kanaroglou. (2011). Three decades of urban growth in the city of Shiraz, Iran: A remote sensing and geographic information systems application. *Cities,* 28, 320–329.

[3] B. Bhatta,S. Saraswati, D. Bandyopadhyay. (2010). Urban sprawl measurement from remote sensing data. *Applied Geography,* 30,731–740.

[4] Abubakr A. A. Alsharif & Biswajeet Pradhan. (2014). Urban Sprawl Analysis of Tripoli Metropolitan City (Libya) Using Remote Sensing Data and Multivariate Logistic Regression Model. *Indian Society of Remote Sensing*, 42(1), 149–163.

[5] Michael R. Muller and John Middleton, (1994), A Markov model of land-use change dynamics in the Niagara Region Ontario, Canada, *Landscape Ecology*, vol. 9 no. 2 pp 151-157.

[6] Sohel Ahmed,Glen Bramle.(2015). How will Dhaka grow spatially in future?-Modelling its urban growth with a near-future planning scenario perspective. *International Journal of Sustainable Built Environment,* 13(6), 133–145.

[7] S. Lauf, D. Haase, P. Hostert, T. Lakes, B. Kleinschmit. (2012). Uncovering land-use dynamics driven by human decision-making. A combined model approach using cellular automata and system dynamics. *Environmental Modelling & Software*, 27-28, 71-82.

[8] Rajesh Bahadur Thapa , Yuji Murayama, (2011), Urban growth modeling of Kathmandu metropolitan region, Nepal, Computers, *Environment and Urban Systems*, 35, 25–34.

[9] Q. Weng. (1999). A remote sensing–GIS evaluation of urban expansion and its impact on surface temperature in the Zhujiang Delta, China. *International journal of remote sensing,* 2001, vol. 22, no. 10, 1999–2014.

[10] Kusuma Sundara Kumar, Pinnamaneni Udaya Bhaskar, and Kollipara Padma Kumari, (2012), Estimation Of Land Surface Temperature To Study Urban Heat Island Effect Using Landsat ETM+ Image, *International Journal of Engineering Science and Technology,* Vol. 4, No.02, 807-814.

[11] Kusuma Sundara Kumar, Pinnamaneni Udaya Bhaskar, and Kollipara Padma Kumari, (2016), Emerging Urban Heat Islands in the New Capital Region of Andhra Pradesh, India - A Satellite based Evaluation, *International Journal of Advanced Remote Sensing and GIS,* Vol 5, No. 10, 1915-1929.

[12] Kusuma Sundara Kumar, Pinnamaneni Udaya Bhaskar, and Kollipara Padma Kumari, (2015), Prediction of Changes in Urban Micro-Climate using Remote Sensing Data and Artificial Neural Network Model, *Wulfenia Journal,* Vol 22, No. 12, 91-112.

[13] D.Kiran Kumar Reddy and SS. Asadi, Evaluation of Environmental Impact Assessment on Industrial Projects: A Model Study. International Journal of Civil Engineering and Technology, 8(1), 2017, pp. 291–301.