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An AI framework for Change Analysis and Forecast Modelling of Temporal Series of Satellite Images

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Abstract—The study focuses on change analysis and predicting future LULC map of capital city of Karnataka state, India. The chosen study area is more prone to urbanisation and greatly affected by population in recent years. Spatial-temporal data from 1989-2019 are considered. LULC classes comprise of Water bodies, Urban, Forest, Vegetation and Openland. An optimal LULC maps from 1989 to 2019 obtained by deep neural network technique are used to perform change analysis which would mainly give the change LULC map with number and percentage of change pixels. According to the analysis performed major change as environmental affecting factor was noticed between 2009 and 2019 where in urban with the area of 189.3861 sq. km remain unchanged and noticeable transitions from other LULC classes to urban. Later, time series classification was performed using Cellular Automata, Cellular Automata-Neural Networks, techniques to predict the LULC map of 2024. Among these CA-NN outperformed with an average kappa coefficient of 0.83. Also, this was validated with projected LULC map of 2024 provided by USGS.

Keywords- Cellular Automata; Artificial Neural Networks; Deep Neural Networks; LULC;

I. INTRODUCTION

Many parts of India are now experiencing the transition from rural to urban since early 2000's which in turn is affecting the environment very badly. This has a great impact on sewage system, air quality, water bodies, increase in greenhouse effect and many other environmental factors [1]. Monitoring this issue is being a challenge from several years. A potent collection of instruments for collecting, storing, swiftly accessing, analysing, and displaying spatial data from the actual world is the Geographic Information System (GIS). Map-making, environmental monitoring, and disaster management can all benefit from the data that can be obtained by Remote Sensing (RS) from airborne and space-based platforms.

An essential tool for management and decision-making is the usage of GIS, RS, with modelling technologies to the arena of environmental protection [2]. There are many benefits to using remotely sensed data from satellites for environmental monitoring. Continuous monitoring and mapping are made possible by remote sensing on both a temporal and spatial scale. Therefore, by heavily utilising remote sensing data and its varied approaches, it is possible to significantly enhance the process of environmental decision-making by regularly monitoring environmental changes and repercussions [6]. Forest monitoring, waterways, agricultural areas, regional and urban planning, changes in Land Use Land Cover (LULC), quality of water and air, mineral prospecting, and natural disasters are few applications of RS-GIS [4]. The detailed list of RS applications is tabulated in Table I.

Table I. Remote Sensing Applications in Environmental Studies. [5]

Meteorology	Hydrology	Natural and Manmade Hazards	Land Use Planning	Ecological Studies
▪ Forecasting weather ▪ Studies related to climate ▪ World-wide Change	▪ Balancing water ▪ Balancing Energy ▪ Moisture content in soil ▪ Agro-hydrology ▪ Sea Surface Temperature	▪ Downpours ▪ Tidal wave effect ▪ Earth Tremors ▪ Landslides mapping and Risk Assessment ▪ Scarcities ▪ Epidemic Mapping ▪ Forest Fires	▪ Land Use/Land Cover Changes ▪ Urban Planning ▪ Urban heat Islands ▪ Agriculture	▪ Pollution causes and effects ▪ Quality of water ▪ Assessment of Climate Change and its' influence on environment.
Soil Science	**Biology/Nature Conservation**	**Forestry**	**Atmospheric Parameters**	**Agricultural Engineering**
▪ Land Evaluation ▪ Soil Mapping	▪ Controlling vegetation mapping ▪ Assessment of green belt	▪ Inventorization of forest ▪ De-/re-forestation Planning ▪ Detection of Forest fires	▪ Aerosol ▪ Fog ▪ Black Carbon ▪ Dust Storm ▪ Ozone and other trace gases	▪ Land use development ▪ Erosion management ▪ Water management

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Our research mainly focuses Land Use Land Cover map analysis. The natural availability of flora, water resources, soil, and other elements on Earth's surface, together referred to as land cover, defines the physical properties of that surface. The use of land by humans and their ecosystems is referred to as land use (such as agriculture, settlements, industry etc.) [7]. LULC analysis forms a major basis in present schemes for monitoring natural resources and environmental changes. Using data from remote sensing satellites, urban land use mapping can be performed and this information can be further utilised for environmental management [3].

Markov-CA and GIS technology have helped with accurate forecasting and successful simulation of spatial changes. By offering basic infrastructure and services, this aids decision-makers in designing sustainable cities. In order to preserve ecological entities and other land uses, this exercise provides local land use planners and city officials with insights into the dynamically growing complex land use system [21].

Change analysis was made on Leipzig city covers urban region of eastern part of Germany using SPOT and LANDSAT images. Post classification approach was adapted and detailed change in amount of imperviousness, Population, Apartments, Cars per 1000 inhabitants, Schools [11] was calculated administrative units from 1994 to 2005.

Landsat 1 MSS, Landsat 5 TM, Landsat 8 OLI [10] satellite imageries of periods 1972,1992 and 2015 respectively were used to perform unsupervised classification using ISODATA technique for the seven capitals surrounding Himalayan region namely Srinagar, Kathmandu, Dehradun, Gangtok, Itanagar, Shimla and Thimphu. It was validated using Google Earth. These maps with built-up land, municipal boundary, population density were used to determine detailed significance of urban growth pattern of these seven cities using Shannon entropy.

Integrated CA models may not be so efficient in addressing socio-economic factors in the simulation process. [13]. Machine Learning models such Support vector machines and Artificial Neural Networks can be used to generate land probability maps, these can be further combined with CA and other dynamic models to improve LULCC simulation.

LULCC monitoring of the great Indian capital, Delhi [9] was done in detail from 1989-2014 using geospatial techniques and cellular automata model by considering growth factors such as slope, population density, distance to CBD and roads and achieved accuracy of 95.62%, area under the receiver operating characteristic as 0.928 between actual LULC and simulated LULC maps. Also the authors have projected the LULC map of 2014 and 2024 to create awareness about ecosystem by predicting the higher urban growth and decreased vegetation in future LULC maps.

The cellular automata are a useful approach for provincial LULC change modelling because it may be used to explore complicated spatial-temporal geographic systems, particularly for provincial land use [19]. A Cellular Automata(CA) model can simulate urban growth based on the idea that past local interactions between land uses have an impact on future patterns of urban growth [12]. Markov Chain (MC) model builds probability matrix to address the transformation happened between land use labels over period of years. But MC alone may fail to represent land use change in spatial dimensions. Combining CA-MC would be a better choice for land use change modelling that could consider both spatial and temporal dimensions.

Integrating CA-MC with Artificial Neural Networks (ANN) [25] would even more capture dynamics involved in land transformations in an efficient manner as ANN is capable enough to extract more relevant features and work on nonlinear data. CA-MC and ANN model was used to project 2021 and 2027 LULC maps in Irbid [12] by achieving higher accuracy.

II. STUDY AREA

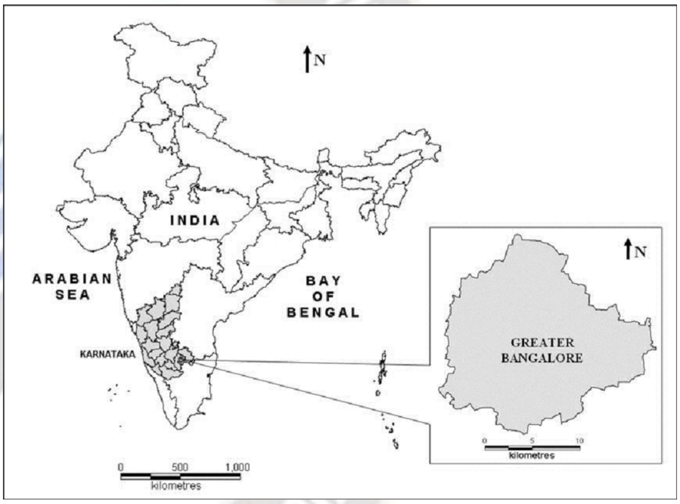

Figure 1. Map of Bangalore [14].

The South Indian Metropolitan City, Bangalore BBMP (Bruhat Bengaluru Mahanagara Palike) limits is considered as the study area in this paper as depicted in Figure 1. Land Use Land Cover Change (LULCC) [7] analysis was made on the Bangalore city, BBMP limits. Main reason for choosing this city is the drastic change in the environment since two decades due to increased urbanisation. The recent observation demonstrates that, in response to growing population pressure [26], human activity has recently grown in higher elevations. The fundamental forces behind the changes can include related policies [8].

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III. DATA USED AND METHODOLOGY

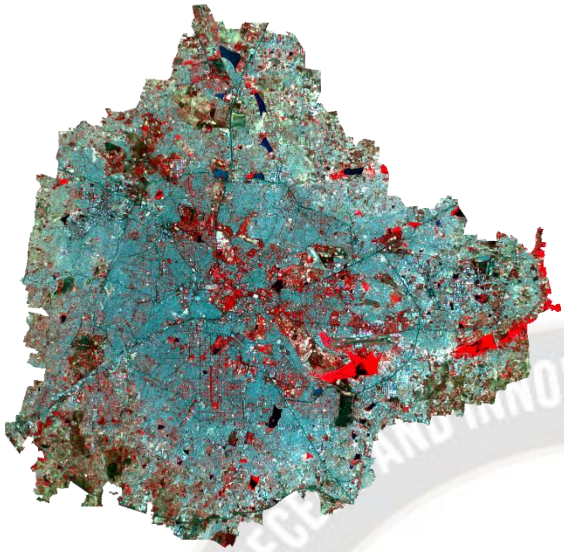

Figure 2. Satellite map of BBMP limits obtained [14].

Data for Bangalore of the period 1989,1994,1999,2004,2009 and 2014,2019 are obtained from Landsat instruments namely 5 and 8 respectively. Suitable JavaScript were used in Google Earth Engine Platform to obtain Landsat data. False Color Composite (FCC) was generated using bands 432(near infrared, red and green) for the landsat 5 TM images. Same way with landsat 8 OLI bands 543(near infrared, red and green) were considered for FCC. One such Landsat 8 of the year 2019 is as shown in Figure 2, which was later clipped using Bangalore BBMP limits shape file using QGIS.

A. Deep Neural Networks

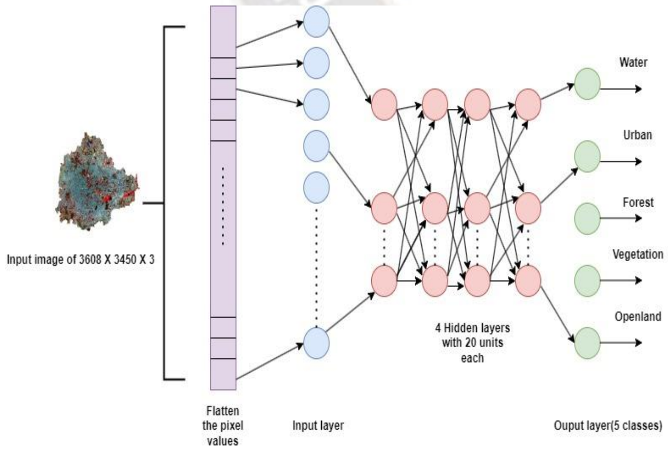

Figure 3. Deep Neural Networks model used. [15]

For each of the temporal series of image mentioned above, training suites obtained from QGIS tool was fed as labelled data to the neural network as depicted in the above Figure 3. Pixel-Based classification [28] approach was employed to generate LULC maps using Python code ran in spyder IDLE, Anaconda framework with NVIDIA GeForce RTX 3090 128 GB GPU. To make the neural networks little complex and get better results, we have added more than three hidden layers and now the model is deep neural networks [27] with 64 units in each layer. Model was built using keras framework. With 50 epochs, we obtained 98.99% as test accuracy. Hyperparameters include batch size of 128, learning rate of 0.0001, droprate of 20% and level l2 regularisation.

B. Change Analysis Procedure

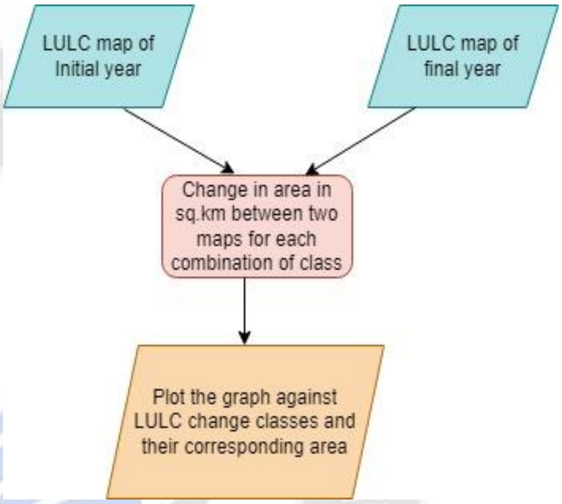

Figure 4. Change Analysis framework

The above Figure 4 represents the steps involved in performing Land Use Land Cover Change Analysis between temporal series of images. Two different periods of LULC maps are given as inputs and then change in pixel values for each class is computed. And also, the transition occurred between a LULC class and with other combinations is measured in the units of area per sq.km.

C. Forecasting LULC using CA-NN model

The next aim of this study was to forecast LULC map of 2024 using cellular automata and deep neural networks model as shown in Figure 5. Cellular Automata (CA) model requires LULC maps of two different periods and growth parameters considered here are digital elevation model map and distance to road map. The non-deterministic nature of urban development regulations is represented by the use of transition rules based on linguistic variabilities [17]. Based on the transition matrix (computed between LULC maps taken as inputs) and the growth parameters influence, threshold is set to determine the LULC class for the next consecutive years'. Thresholds set can be varied for LULC classes and growth parameters to get optimal forecasted maps with less error rates.

The CA model can be stated as in equation. (1).

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$$S(t, t+1) = f(S(t), N) \quad (1) \quad [20]$$

where t and t + 1 denote the various periods, S is the set of finite and discrete cellular states, N is the cellular field, and f is the rule for transforming cellular states in local space.

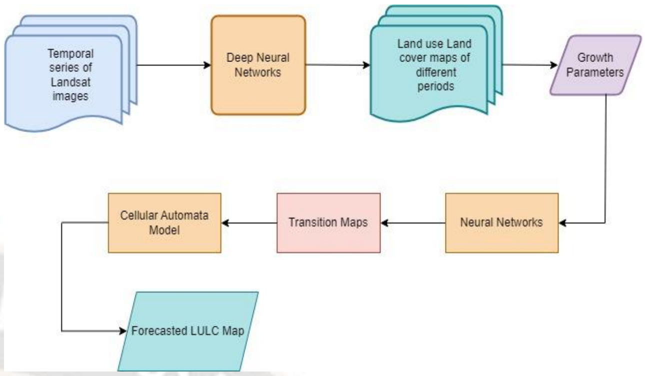

Figure 5. Proposed Cellular Automata and Neural Networks Model.

Further Neural network (NN) model as shown in Figure 3 was integrated with CA model to reduce the validation error and to improve the accuracy by predicting the LULC map with suitable training suites as NNs are modelling tools that excel in resolving nonlinear issues [16]. Same hyperparameters were used as utilised in generating optimal LULC maps [15].

For the validation of the predicted LULC map by CA-NN model, Kappa coefficient metric used as mentioned in equation. (2).

$$\text{Kappa} = \frac{P_0 - P_A}{1 - P_A} \quad (2) \quad [18]$$

where P_0 is actually observed and P_A is chance agreement.

The range of the kappa coefficient is zero to one, with one denoting a thorough and accurate categorization, 0 an arbitrary categorization, and a negative value denoting misclassification [19].

The most significant results of this study are that the CA-Markov algorithm performs better in calibration process while the NN algorithm performs better in forecasting those phenomena with less prediction error rates. [22].

IV. RESULTS AND DISCUSSIONS

LULC maps generated by deep neural networks [15] for the temporal series of Landsat images with the optimal band combination as mentioned in the Figure 6. Considered LULC classes are Water bodies, Urban, Forest, Vegetation and Openland.

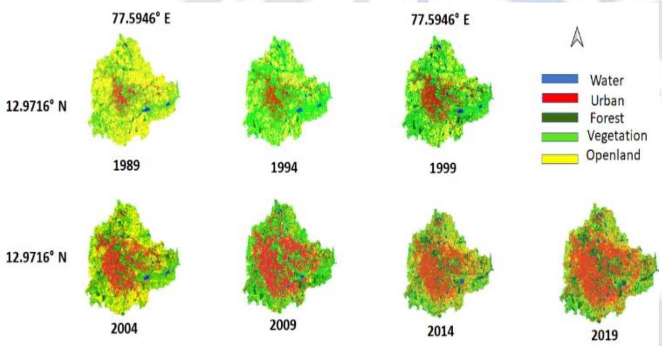

Figure 6. LULC maps obtained using deep neural networks for the temporal series of Landsat images for the years' 1989,1994,1999,2004,2009,2014 and 2019.

A. Change Analysis

Bangalore is popularly known as Silicon City, which is more prone to urbanisation since two decades. This has tremendous effect on environment which would be major focus of this research paper. Urbanisation factor leads to severe issues in the city with regard to infrastructure, roads, sewage and others. The figures from 7-12 depict changes [24] for the land use land cover classes such as Water body, Urban, Forest, Vegetation and Openland for the temporal series of Landsat images from 1989 with the interval of 10 years till 2019.

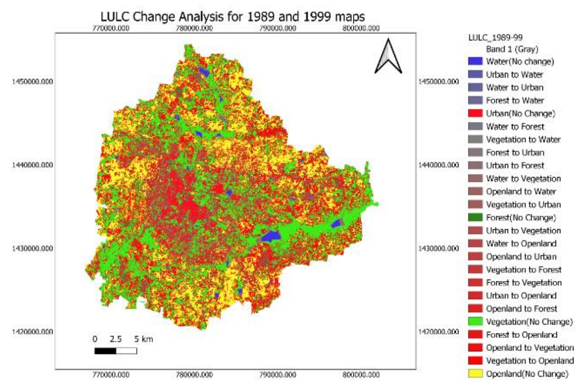

Figure 7. LULCC analysis between 1989 and 1999.

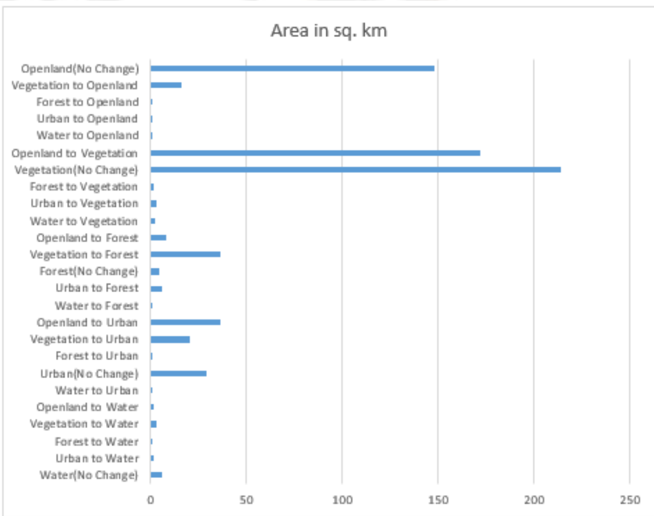

Figure 8. Horizontal bar graph against Area in sq. km and LULC classes between 1989 and 1999.

The noticeable change in the LULC maps of 1989 and 1999 was the conversion of vegetation to urban (20.5875) and openland to urban (36.5202) in the unit of area in sq. km. The same is depicted in the graph. Area wise for openland and

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vegetation classes remain unchanged. Most of the uncultivated land portion was converted to green area.

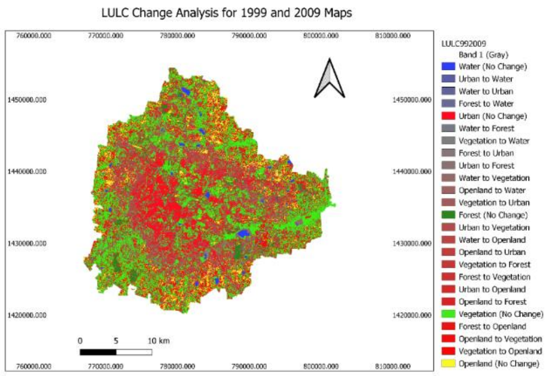

Figure 9. LULCC analysis between 1999 and 2009.

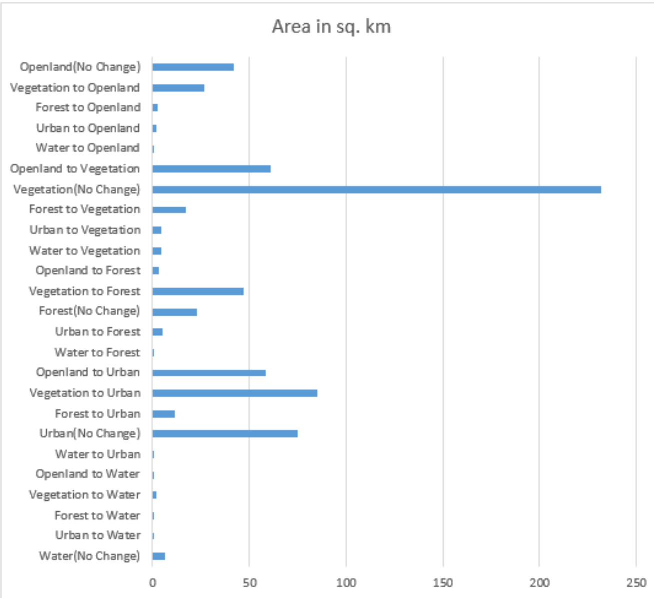

Figure 10. Horizontal bar graph against Area in sq. km and LULC classes between 1999 and 2009.

The major environment affects between 1999 and 2009 was vegetation to urban and openland to urban with the area coverage of 85.0095 and 58.3281 in sq.km respectively. Agricultural land remains same and there are few portions of open space transformed to vegetation area.

As the below graph depicts that urban cover of 189.3861 in sq. km represents no change in the LULC maps of 2009 and 2019. The most environment affecting transformations were between vegetation to openland, vegetation to urban and openland to urban.

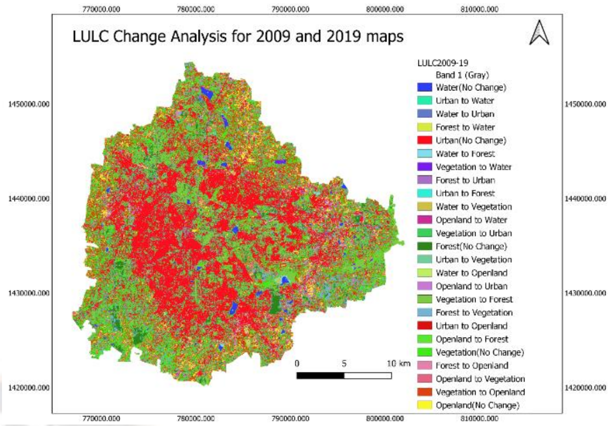

Figure 11. LULCC analysis between 2009 and 2019.

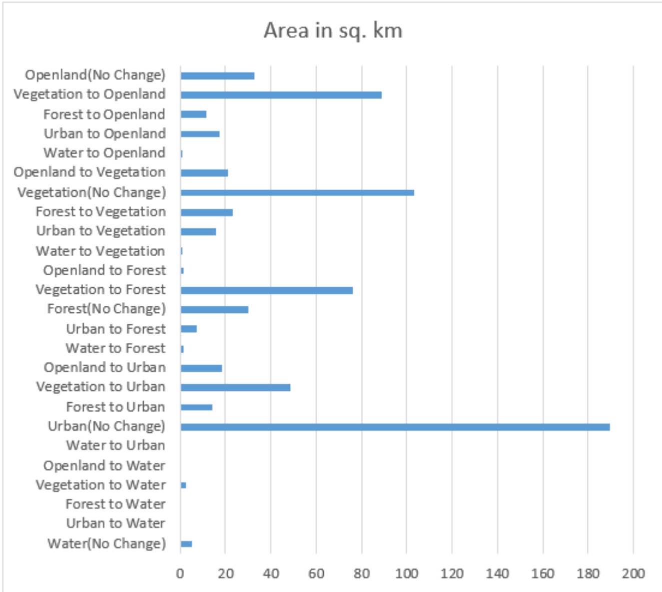

Figure 12. Horizontal bar graph against Area in sq. km and LULC classes between 2009 and 2019.

B. *Forecasting LULC map*

The following Figure. 13 shows the actual and predicted LULC maps of different temporal series. To obtain LULC map of 1999, 1989 and 1994 LULC maps were used as inputs along with DEM and distance to road as support factors with an interval of 5 years between each image. Likewise, 2004 obtained from 1994 and 1999 and so on till 2019. Here, actual LULC maps are satellite based. Predicted maps are the results of CA-NN model. An overall accuracy of 78% achieved with trial and error method in setting threshold for previous periods of LULC and growth factors.

Table II. Cohen's Kappa Coefficient Interpretation [23]

Range of Kappa	Agreement level	Reliability of data used
0.00-20.00	None	0-4%
0.21-0.39	Minimal	4-15%
0.40-0.59	Weak	15-35%
0.60-0.79	Moderate	35-63%
0.80-0.90	Strong	64-81%
Above 0.90	Almost Perfect	82-100%

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As per table II standard values, range of Kappa coefficients obtained in our study lie in the strong level and agreement seems to be substantial.

Table III. Kappa Coefficient obtained between Actual and CA-NN simulated LULC Maps.

Year	Overall Kappa Coefficient
1994	0.88
1999	0.82
2004	0.81
2009	0.81
2014	0.80
2019	0.87

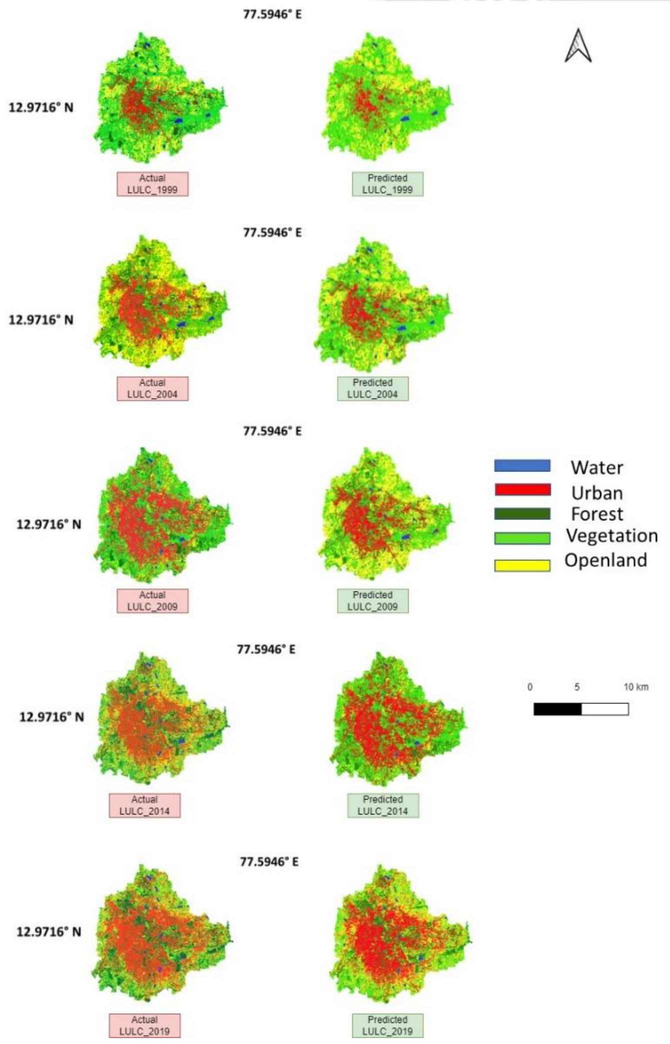

Figure 13. Actual and Predicted LULC maps obtained for different temporal series of LANDSAT images using CA-NN model.

Forecasted LULC map of 2024 used 2014 and 2019 LULC maps as inputs with growth factors. The map shown in Figure 14 was validated with land cover map of the same year obtained from USGS and the results of the same are tabulated in Table III.

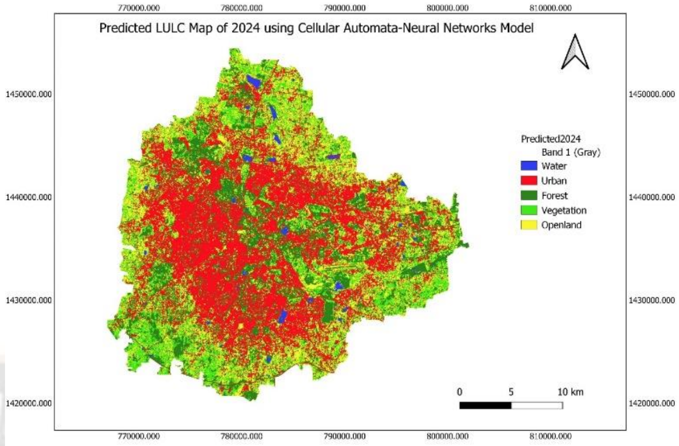

Figure 14. Forecasted LULC map of 2024 using CA-NN model.

V. CONCLUSION AND FUTURE

Land use land cover maps form the foundation for urban planning, natural resources conservation, forest monitoring etc. This study addressed optimal deep learning techniques to generate land use land cover maps of silicon city, Bangalore, state of Karnataka, India. Change analysis from 1989 till 2019 were made to know the effect of urbanisation which in turn badly affects environment and natural resources.

Finally, forecasted land use land cover map of the year 2024 generated with the integration of neural networks and cellular automata gave clear picture of built-up growth which is increased up to 5% and no transformation of urban class to other classes as compared to previous temporal period 2019 and witnessed urban expansion. This analysis was done mainly to create awareness in the society for conserving natural resources for the next generation. Further, forecasting model can be optimised with deep learning techniques.

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