# Urban Growth Modelling Based on CA-Markov Approach on Bengaluru India

Jyothi Gupta[1][a] and Raghunandan Kumar[2]
[1]*School of Architecture, CHRIST (Deemed to be University), Bengaluru, 560074, Karnataka, India*
[2]*Department of Civil Engineering, CHRIST (Deemed to be University), Bengaluru, India*

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Abstract: The theme of this research is to create spatial patterns for Bengaluru city in India to understand the urban growth over the past 40 years. The problem of our re-search addresses developing an integrated Geospatial Modelling Approach to as-sess Urban Growth patterns in Bengaluru Metropolitan Region. This study uses the various logical methods to create the Land Use/Land Cover (LULC) Map, all the datasets in google earth engine are categorised in the Supervised Classification. Machine Learning Processes such as Random Forest (RF), Classification and Regression Tree (CRT), and Support Vector Machine (SVM) classifiers are considered for this Classification. The Classifier's performance is evaluated using statistical measures like overall Accuracy and kappa statistics. Classes with multiple parameters are carried out with the Hybrid Cellular Automata- Markov (CA-Markov) method, which is capable of duplicating changes through one grouping to another. This hybrid model supports model both spatial 3D and temporal time-based changes. The main product after modelling predicts LULC for 2041 and 2051. The argument is that CA-Markov, Shannon entropy will allow us to define how much area of all classes will be changed in 2041 and 2051.

## 1 INTRODUCTION

Land use is a phrase that is referred to how humans use the land and its resources, as well as the purposes for why they do so. The environment or vegetation type present, like forests or farmland, is referred to as land cover. Artificial changes in the earth's crust are referred to as land use/land cover (LULC), often called land change (Bhat et. al, 2015). Landcover use has been identified as a fundamental cause of climatic change on geographical and time dimensions, appearing as a critical environmental concern and one of the major research initiatives on global change research on a local scale (Baqa et al, 2021).

## 2 AIM AND OBJECTIVES

AIM: To develop a cohesive CA-Markov Model Approach to assess Urban Growth patterns in Bengaluru Metropolitan Region.

*Objective of the Study*: Visualize and analyse the Spaciotemporal transformation in Land use /Land cover (LULC) from -1991,2001,2011,2021(40 years). Simulate the past LULC and forecast the future development of the Bengaluru Metropolitan Region using CA Markov Model 2031, 2041.

Identifying Specific Regions where intense Urban Growth can occur in Bengaluru Metropolitan Region.

Table 1: Methodology Flow using Google earth engine.

| Google earth engine (GEE) | Export Landsat images in tiff format | Creating train/test data for class | Use of Classifier | Train the classifier using train data | Classify as image or feature selection |
|---|---|---|---|---|---|
| Data catalog | | DEM | OSM Data | (Road layer) | |
| Landsat 5,7 and Sentinel-2 Data from | | Slope, Aspect | Euclidean distances | On roads and Urban | |
| Image pre-processing | | LULC change analysis | LULC change matrix | | |
| Supervised LULC | | Transition Potential | Transition Potential Map | Reference Maps | |

[a] https://orcid.org/0000-0003-0612-0188



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| | | | | | |
|---|---|---|---|---|---|
| classification | | Modelling (MLP) | | | |
| Accuracy Assessment 91,2001,21, 21 | | CA Markov Simulation | Model Validation for 21 | Calibrated CA-Markov Model 31-41 | Predicted LULC maps |

The table 1 shows the flow in methodology, which is used in this study.

# 3 DATA COLLECTION

The Remote Sensing Data of LANDSAT Multispectral, TM, ETM+, and OLI/TIRS & Sentinel-2 MSI: Multispectral Instrument, Level-2A data is used for Supervised Classification such as Random Forest (RF), Classification and Regression Tree (CRT), and Support Vector Machine (SVM) in Google Earth Engine (GEE). Using these datasets, land use land cover (LULC) for 1991,2001,2011,2020 are Simulated in Google Earth Engine. Digital Elevation Model (DEM) from Earth Data by NASA is Downloaded in table 1-2. The Digital Elevation Model (DEM) Slope is Generated in ArcGIS Pro. The Slope gives the identification of terrain, whether the Terrain is Steep or flat (Mishra et al, 2014). The low slope value will have flat terrain, and a high slope value will have steep terrain. From the Slope, the aspect is generated. The aspect identifies the downscale direction of a high-value change rate through one cell towards its neighbours. Road Layer has been obtained from the Open Street map. Euclidean Distance to Roads and Railways are Considered. Euclidean Distance to Built-up is also considered. Table 2 is created to show the link attachment.

Table 2: Data collection from Online link.

| Year | Data | *GEE Spatial resolution / Link* |
|---|---|---|
| 1991 | Landsat 5 Series TM AND ETM - GEE | *30 m* |
| 2001-2011 | Landsat 7 Series TM AND ETM - GEE | *30 m* |
| 2021 | Sentinel – 2 GEE datasets | *10m to 60 m* |
| | Administrative and city boundary | *Shapefile-https://www.diva-gis.org/* |
| | DEM (Digital Elevation/Terrain model) for Slope and Aspect | *Earth Data - https://earthdata.nasa.gov/* |
| | Census data for 4 decades | *Census of India https://censusindia.gov.in/* |
| | Road network and Railway | *Open Street Map https://www.openstreetmap.org/* |

# 4 CA-MARKOV MODEL

The CA-Markov model a hybrid model which develops the traditional Markov model with the Cellular Automata model (CA). The CA methods are utilized to regulate the spatial dynamics of the GIS platform (Jain et al, 2016). The spatiotemporal raster Based da-ta modelling is employed to show what has changed for constant data over time across Land use/land cover categories using transition probabilities. When it comes to land-use change projections, the Markov model concentrates upon quantity (Jadawala et al, 2021). The spatial parameters of this model are inadequate and don't account for the different forms of land use types of variations in the spatial magnitudes. The CA model prepares a robust area conception; this means it can handle complex space systems in terms of space-time dynamic evolution (Yadav et al, 2021). The CA–Markov model, which combines Markov and CA theories, is concerned with time series and space for prediction purposes. This could effectively simulate changes in quantity and space of land use patterns throughout time and space. The LULC maps were created using the Google Earth engine, then exported as Geo Tiff files and divided into four categories. Water is in class 1, Vegetation is in class 2, Barren is in class 3, and Built-up is in class 4. These LULC maps were converted into rst format from Geo Tiff Format in Clark Labs TerrSet IDRISI software. The land change modeller(figure1-3) helps to make the forecast LULC diagram centred on equally the previous LULC map and future LULC plan.

This panel in figure 1 creates several Transitional maps. Changes, persistence, gains, and losses can be mapped by land use/cover class, as well as transitions and transfers by class. Change patterns in environments influenced by hu-man intervention can be complex and challenging to recognize. A geographic trend analysis tool was developed to aid understanding in such circumstances. This is the polynomial trending surface that best fits the changing pattern. A call to a TREND module analyzes this choice as show in figure 1a.

To Predict 2031 & 2041 Land Use Land Cover, Clark Labs TerrSet IDRISI software was employed in 2 ways to build transition areas & transition area probability matrices.

For LULC change analysis, the Land use/Land cover Change module software Land Change Modeler (LCM) is employed. The Change Module investigates the difference among two LULC photos, namely the previous and latter land cover photographs as show in in figure 1b. All the Parameters should be converted to

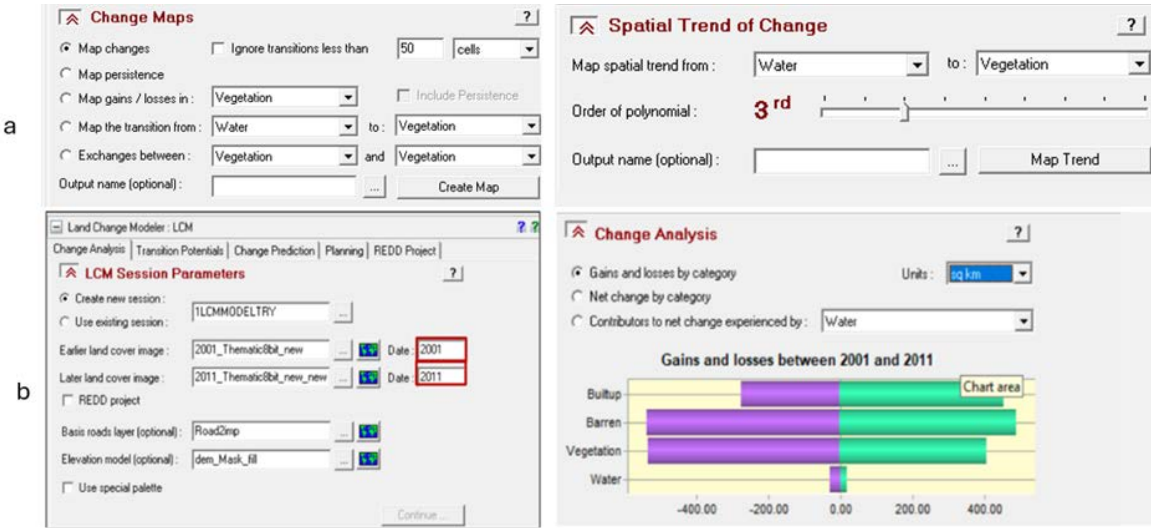



Figure 1: (a) Changes in map and Spatial trends and (b) Change analysis's and LCM parameters.

rst for-mat from Geo-tiff Format in Land Change modeler.

Clark Labs TerrSet IDRISI software will estimate LULC parameters based on previous and current Land use/land maps to generate Change possibility matrix reports that reflect the chance of both LULC class transitioning to alternative session.

Secondly, a CA-Markov model has helped to forecast the Transition in the LULC categories for 2031 and 2041. Additionally, with the use of two LULC maps created from satellite photographs. The model is used to determine the set of a random process, X (t), at every point in time-period, t1, t2, tn,tn + 1; consequently, the unplanned processes will explain in equation 1.

$$FX(X(tn)) = xn, X(tn-1) = xn-1, X(t1) = FX(X(tn)) = xn \quad (1)$$

tn shows the present time and tn+1 denotes time in future; t1, t2, t3, t4……, tn − 1 implies continuous time frame moments in the previous time. According to current realities, the future remains independent of the previous time. Hence, the future random process is not affected by someplace it occurs. It is not where it used to be or where it is today. If M[k] is the Markov chain, and xn is a group of N states (x1, x2, x3….. xn), The chance of Transition between condition i to condition j for single time instant is given by Equation 2.

$$P_{i.j} P_r(M[k+1] = j | M[k] = i) \quad (2)$$

The Land Change Modeler module provides three techniques for constructing transition potential maps associated with sub- models and independent Parameters: a multi-layer perceptron (MLP) neuronic network link, logistic regression, and a machine learning tool like similarity -weighted instance (Sim-Weight). The MLP correctly forecasts the plot that will transfer since the picture of a subsequent stage to the indicated simulated period, depending on the projections. MLP surpasses alternative strategies in estimating the correlation among nonlinear land-use / land cover LULC changes and explanatory variables in equation 3-4. When several transition types are modeled, it is more versatile and dynamic than the others.

$$S(t+1) = P_{ij} \times S(t) \quad (3)$$

where 0 ≤ Pij < 1 and n ∑ j=1 Pij = 1, (i, j = 1, 2, . . ., n).

The following formula is used to definite the CA cellular automata model:

$$S(t, t+1) = f[S(t), N] \quad (4)$$

where S(t) and S(t+1) are the organization rank at periods t and t + 1, correspondingly. N represents the cellular field, t, t + 1 represent distinct intervals, f symbolizes the transforming rule of cellular conditions in a particular region, S represents the group of restricted and distinct cellular conditions, and Pij represents the evolution probabilities in a phase.

## 5 SHANNON ENTROPY (HN)

Shannon Entropy is a commonly used metric of spatial dispersion or concentration that is widely used in the research of the urban sprawl phenomenon. The Hn measurement depends on the entropy concept, which was first designed to quantify information. It is a valuable and dependable metric for deciding the level of compactness & dispersion of urban expansion.

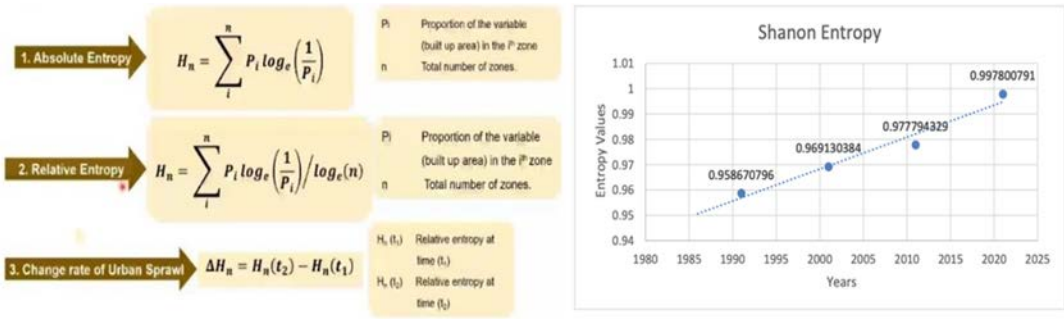



Figure 2: Shannon Entropy Equation & Obtained results.

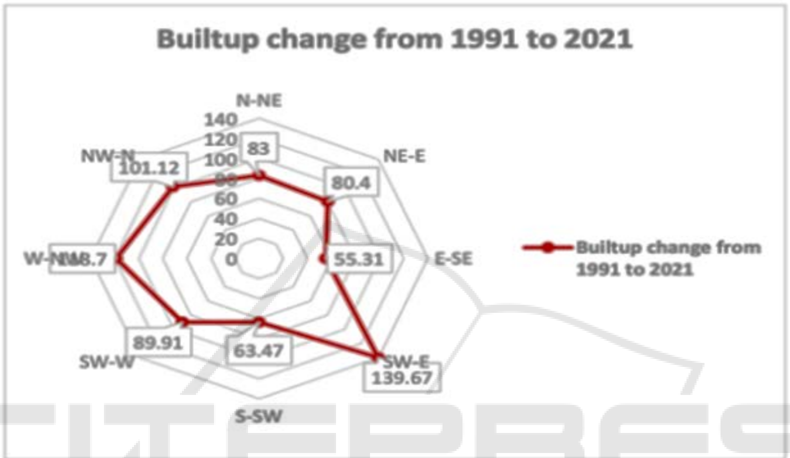



Figure 3: Built-up changes and Line graph for Shannon Entropy.



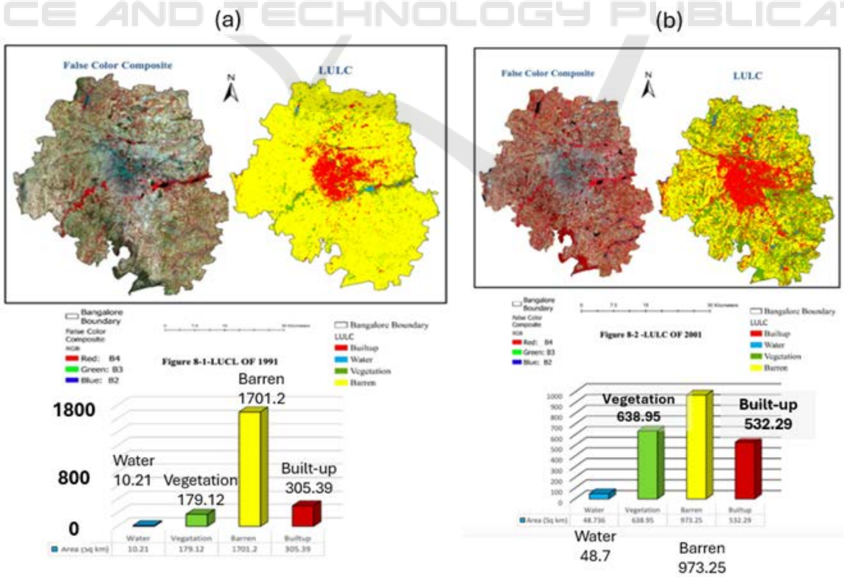



Figure 4: Spatial Urban pattern LULC showing growth (a) 1991, (b) 2001,2022,2021.

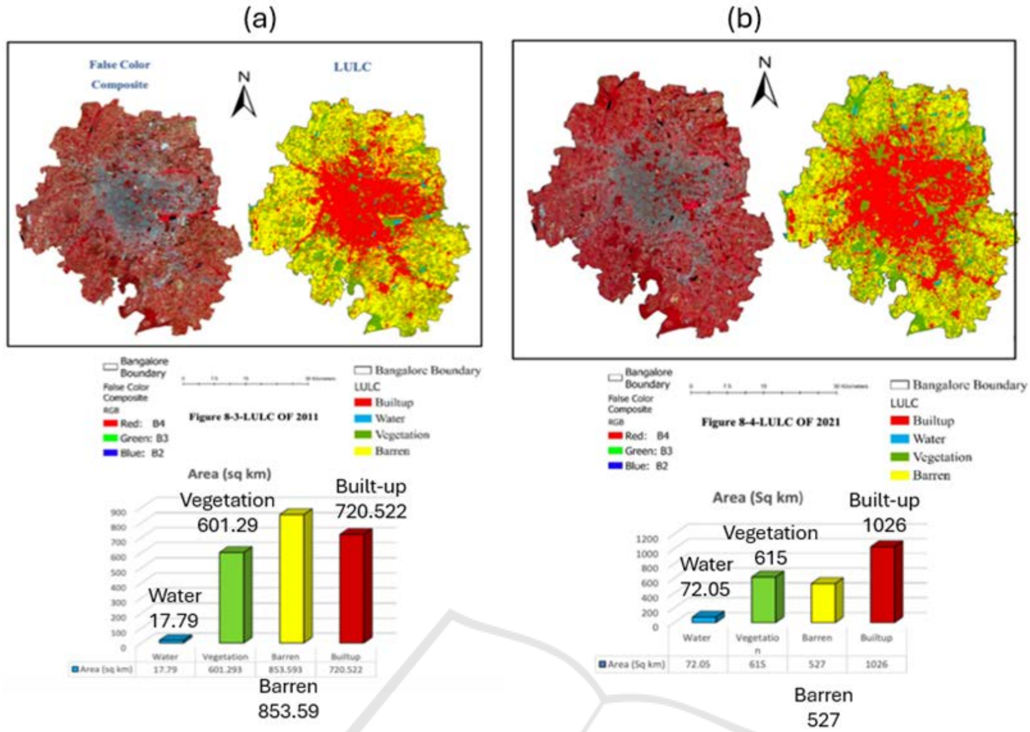
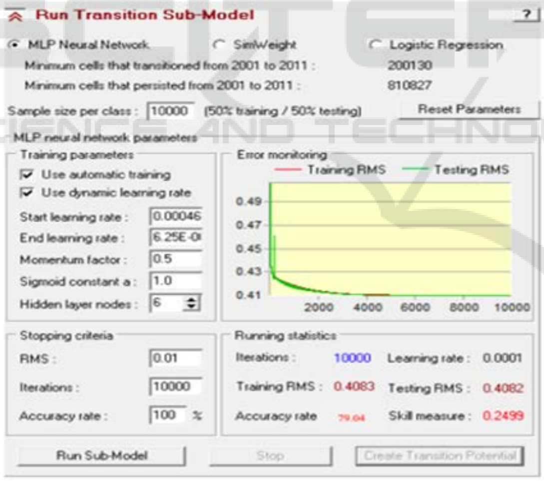
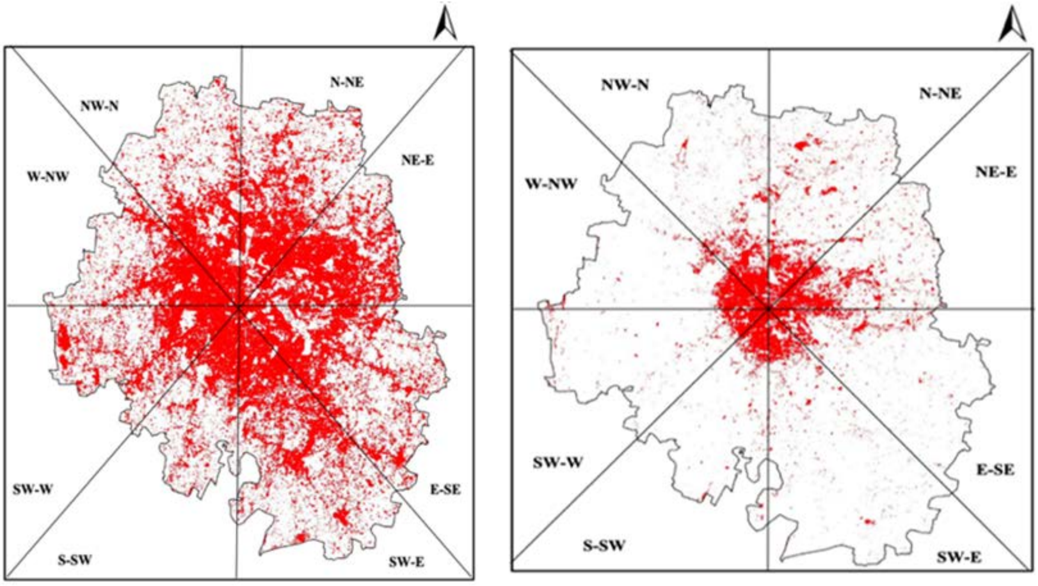



Figure 5: Spatial Urban pattern LULC showing growth (a) 2021, (b)2022.




| | |
|---|---|
| Input layer neurons | 11 |
| Hidden layer neurons | 7 |
| Output layer neurons | 4 |
| Requested samples per class | 10000 |
| Final learning rate | 0.0001 |
| Momentum factor | 0.5 |
| Sigmoid constant | 1 |
| Acceptable RMS | 0.01 |
| Iterations | 10000 |
| Training RMS | 0.2447 |
| Testing RMS | 0.2453 |
| Accuracy rate | 79.04% |
| Skill measure | 0.7205 |

Figure 6: Model Accuracy.




(a) (b)

Figure 7: Bangalore Builtup area (a) 2001 (b) 1991.

Where Pi is the fraction of a geophysical parameter in i-th zone and n symbolises the overall sum of zones as seen in figure 2. The entropy value can range amid 0 and log (n). A number around 0 implies a relatively tight circulation, while a value close to log(n) show a scattered distribution. The mid-level of log(n) is regarded as the threshold level; hence, a city with just an entropy value higher than the threshold value is referred to be a spreading city. From 1991 to 2021, the most significant shift has occurred in the Southeast direction, where the Built-up area has urban growth as shown in figure 3-4.

We can see the Spatial Change patterns of Bengaluru's significant barren land from 1991 and how it changed to a built- up area in 2021 due to urban sprawl. We can see the patterns of change analysis of how vegetation increased from 1991 to 2021 and how it progressively reduced and then rose. Gains and losses, change transitions, and change analysis are patterns we've seen where substantial barren land has been turned into Urban land.CA Markov is the most common and effective modeling method for many researchers who often use for modeling urban growth.

We forecasted forthcoming LULC land use/land cover for 2031 and 2041 using the CA-Markov model, and we have calculated the future Area in sq-km of all classes. Which will aid in identifying where and in which direction built up would increase and which city planners can use to prepare for future expansion.

The dynamic learning process begins with a strong learning rate but decreases gradually over repetitions till the last knowledge proportion is stretched at what time the highest sum of repetitions is extended. If a huge fluctuation in the RMS inaccuracy is found during the first number of reiterations, the learning rates (begin and finish) are condensed by part, and the technique is repeated in figure 6. LCM keeps the MLP's (Multi-layer Perception) other variables at their default settings. On the other hand, LCM does not make any specific changes to outputs. Because changes are being simulated, LCM filters out any circumstances that do not meet the context of any given transition from the transitional potentials. In figure 3 if the change is from Barren to Vegetation, values will only occur in a pixel before Barren, then Transition potential maps are generated. The dynamic learning process begins with a strong learning rate but decreases gradually over repetitions till the absolute learning rate is extended once the extreme sum of iterations is gotten. If a enormous fluctuation in the RMS mistake is found during the first number of iterations, the absorbing charges (begin and finish) are abridged by quasi, and the procedure is repeated. LCM keeps the MLP's (Multi-layer Perception) other variables at their default settings. On the other hand, LCM does not make any specific changes to outputs. Because changes are being simulated, LCM filters out any circumstances that do not meet the context of any given transition from the transitional potentials. In figure 7 if the change is from Barren to Vegetation, values will only occur in a pixel before Barren, then Transition potential maps are generated.

In 1991, Barren Land accounted for around 75 % of the overall Bengaluru District Boundary, while Vegetation accounted for 9.2 %, and built-up area accounted for 15 % of the total Bengaluru District Boundary. Then, in 2001, we can see that bare land decreased to 30.7 %, while built-up has expanded 9.2 % since 1991 and Vegetation rose exponentially to 29.2 %. Between 2001 and 2011, barren land was reduced by 8%, and Vegetation was decreased by 4%, resulting in an 8.2% increase in an urban area in 2011 as barren plot was transformed into the urbanized area. From 2011 to 2021, barren land was reduced by 14.81%, and Vegetation has been increased by 2%, resulting in a 13.9 % increase in an urban area in 2021 (figure 5-7).

Because the Accuracy of the Land Change Modeler is 79.02 percent, we can claim it will predict about 80 percent of the time. As shown, Bengaluru's future urban growth and the direction in which the city is expanding are visible.

Between 2021 and 2031, bare land will be reduced by 5.78%, and Vegetation will be reduced by 4%, resulting in a 7.88% increase in urban areas in 2031. The total built-up area will increase by 54.6 %. Between 2031 and 2041, bare land will be reduced by 4 %, and Vegetation will be reduced by 2%, resulting in a 6.4 % increase in urban areas in 2041. The total built-up area will increase by 61 %.

## 6 CONCLUSIONS

Using Shannon Entropy, we can see that the most substantial change from 1991 to 2021 happened in the Southeast direction, where the Built-up region has increased. This study concludes the challenges and issues of urbanization in Bengaluru (Gupta J, 2022). The solutions to these concerns are GIS data and raster data are employed. Raster data are collected from the google earth engine & GIS Data are gathered from different web portals & studied various research literature in the journal about the problem. To bring this study to a close, qualitative, and quantitative tools were examined. This paper explains the logical method, which must be associated with the CA Markov Model and the Shannon Entropy Study.

This report requires Future research of Bengaluru's changing spatial patterns of urban growth. It is challenging to identify significant differences between agriculture and parks because of the low spatial resolution of Landsat 5 & 7 (Gupta et al, 2015). The CA Markov model has a drawback in that it cannot be employed for short time intervals. While calibration is the most crucial procedure for determining which parameters are appropriate for the model, this model has been run more than 15 times. Each time the parameters change, the results vary.

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