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DECADAL TRANSFORMATION OF LAND USE - LAND COVER AND FUTURE SPATIAL EXPANSION IN BANGALORE METROPOLITAN REGION, INDIA: OPEN-SOURCE GEOSPATIAL MACHINE LEARNING APPROACH

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ABSTRACT:

Land use and land cover (LULC) are the terms by which we can denote how the people are utilising the land to serve different purposes and what covers the earth's surface, respectively. This study will present LULC changes and future spatial expansion of the Bangalore Metropolitan Region (BMR), which comprises of Bangalore urban district, Bangalore rural district, and Ramanagara district. The Bangalore metropolitan region is spread across an area of 8005 sq. km and is undergoing a phase of rapid population expansion, which causes increasing concrete space and decreasing green space. This study will focus on achieving the following objectives: Comparing the Spatio-temporal changes, accessing the pattern of expansion, future projection of LULC pattern in Bangalore Metropolitan Region, and finding how the population growth impacts the land use changes. The study is based on an urban expansion model for the years 2030 and 2050 in BMR. The study has used two add-on tools, i.e., the Dzetsaka classification tool and Modules for Land Use Change Simulations (MOLUSCE) in QGIS, to generate the land cover transformation. The core upshots of this technique show the land use and land cover transformation, and urban expansion pattern in the Bangalore Metropolitan Region. It also illustrates the Spatio-temporal changes and how dispersion or expansion has occurred in the last five decades and predicts the future three decades changes. The results are expected to aid society and several organisations such as city planners and policymakers.

1. INTRODUCTION

Change is the rule of the world. Land use and land cover (LULC) experience one of the most dynamic changes in a habitat. Land use can be referred to as how human society utilises the land around them and land cover can be referred to as how the lands are occupied by forest, water bodies, soil, snow, grassland, etc. Every year there are new changes in LULC and these changes greatly affect the study of an area. Changes in LULC may not be an essential part of human life, but it greatly influences built-up areas, change hydrological processes such as runoff patterns, peak flow characteristics, water quality, and so on (Ashaolu et al., 2019), which in turn impacts the natural course of the environment. Therefore, Spatio-temporal studies are imperative. LULC studies are generally adopted to know the change in the ecology of the area and vegetation (El-Tantawi et al., 2019). Mapping LULC change has been determined as an essential aspect of numerous activities and applications, such as in planning for land use or global warming mitigation (Talukdar et al., 2020). Humans are one of the major factors responsible for these changes and humans are the only ones who study these changes to develop rational conclusions. Remote sensing and GIS make it easier to study the changes as well as to make rational decisions. Remote sensing aid in the capturing of LULC information and its aftermath on climate, biodiversity, fluvial and existing topography i.e., remote sensing helps in monitoring and acquiring information, and GIS aids in the capturing, storing, manipulating, analysing, and modeling the information acquired by remote sensing. Studying the Spatio-temporal changes in LULC with the help of remote sensing and GIS provides us with an end number of options for LULC modeling. It aids in monitoring the changes and further predicting the changes shortly, providing the substructure for land management.

It gives us a picture of how LULC changes increase or decrease the area occupied by certain classes. LULC classification can be performed through two processes i.e., Supervised and Unsupervised classification. There are multiple approaches to executing supervised classification, such as Maximum Likelihood (Yesuph and Dagnew, 2019; Chaudhuri et al., 2017), Minimum Distance, Parallelepiped, and Support Vector Machine (SVM) (Rudrapal and Subhedar, 2015). This study applies the Support Vector Machine (SVM) approach in QGIS to carry out the LULC supervised classification of BMR as it produces the highest accuracy among all the other approaches (Abdul et al., 2020). Researchers around the world in the current global scenario are indulging themselves in diverse research and practising different models to generate their expected outcomes (Hasan et al., 2020; Liu et al., 2019; Baig et al., 2021; Rishma et al., 2019; Bugday and Bugday, 2019).GIS provides several LULC change prediction models such as IDRISI's CA MARKOV (Abdul Rahaman et al., 2017), CLUE-S/ Dyna CLUE (Katawut and Parichat, 2020), DYNAMICS EGO (Lin-lin Cheng et al., 2020), Land Change Modeler (Jatin Anand et al., 2018), and MOLUSCE (Kamaraj and Sathyanathan, 2021).

This study uses the MOLUSCE (Modules of Land Use Change Evaluation) plugin in QGIS, which is being created to analyse, mould and simulate the LULC changes. It is much user friendly and contains a variety of modules and functions and is composed of many components such as an input module, an analysis of the changing trend, transition modeling, prediction, and validation (Kafy et al., 2021). It assists in computing the land use and landcover changes between two time periods and prepares the simulation model for a future period. It includes in-built four algorithm models i.e., Artificial Neural Networks (ANN) Multi-layer Perceptron, Multi-Criteria Evaluation (MCE), Weights of Evidence, and Logistics Regression. This

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study uses the ANN multi-layer perception algorithm, which forecasts classified images using supervised classification and creates simulated 2030 and 2050 LULC changes map and predicts the same by taking into reference the various input spatial variables. The spatial variables include grided population data, SRTM data, road and railways data. The study has the following objectives: Comparing the Spatio-temporal changes, accessing the pattern of expansion, future projection of LULC pattern in Bangalore Metropolitan Region, and finding how the population growth impacts the land use changes.

2. DATA AND METHODOLOGY

2.1 Study Area

The Bangalore Metropolitan Region (BMR) comprises Bangalore urban, Bangalore rural, and Ramanagara district. It extends between 12◦ 14' N to 13◦35' N latitude and 77◦05' E to 78◦ E longitude with a total area of 8005 sq. km (Fig. 1). It lies in the south-eastern part of Karnataka state. It is surrounded by the Kolar district in the east, Tumkur and Chikkaballapura to the north, Mandya district to the West, and Chamarajanagar and Tamil Nadu to the south. It has an average elevation of 920 m with the highest point in Doddabettahalli with a height of 962 m. It experiences a tropical climate with January being the driest month and October being the wettest month with an average rainfall of 147 mm, April being the warmest month recording an average of 26.6◦C, and December recording the lowest temperature of an average of 20◦ C. It is predominantly covered by red soil making it possible to grow crops such as millets, pulses, fruits, rice, oilseeds, bajra, and so on. The region doesn't have any major river system but a small tributary of river Kaveri, Arkavathi originating from Nandi Hills in Chikkaballapura flows through it and joins Kaveri near Mekedatu.

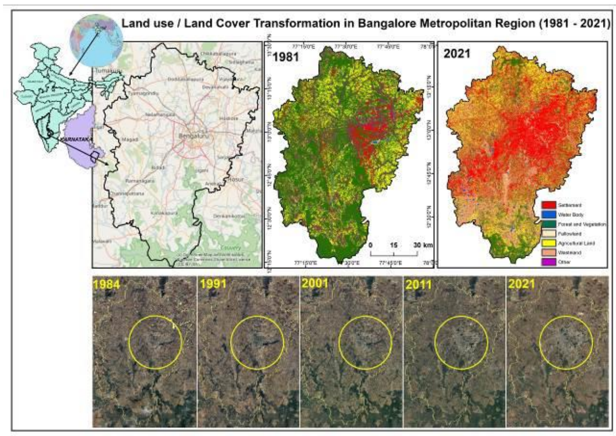

Figure 1: Study area

2.2 Dataset and Criteria

The study is based on an urban expansion model for the years 2021, 2030, and 2050 in BMR. It has used suitability parameters to find the prediction / simulate the land use scenario such as roads, railway lines, drainage pattern, socio-economic condition, population density, and topographical condition of the region. Along with this, it has also performed Normalized Difference Built-up Index (NDBI) to understand the growth of urban areas. For this study, satellite imageries were utilised from the Landsat dataset, IRS, and Sentinel-2A. Landsat imageries are taken down from google earth explorer, IRS data from Bhuvan, and Sentinel 2A from Copernicus open access hub. The satellite imageries of the year 1981 is extracted from Landsat 2 (MSS) with 60m resolution, the year 1991 imagery is taken from Landsat 5 (TM) with 30m spatial resolution, for the year 2001 Landsat 7 (ETM+) image with 30 m spatial resolution. 2011 imagery is taken from IRS LISS-III (Indian Remote Sensing, Linear Imaging Self-Scanner) with 24.5m spatial resolution, and the year 2021 SENTINEL 2A Multispectral Instrument (MSI) image with 10 m spatial resolution is being used. The DEM data were extracted from SRTM (Shuttle Radar Topography Mission) with a spatial resolution of 30m, from which the elevation and topographical condition are extracted. The roads and railway networks are extracted from Diva GIS, updated with the Survey of India topographic sheet, and google earth according to the land use year. The population data for the years 2011 and 2021 is taken from the population grided data.

2.3 Methods

The present study uses QGIS plugins and add-on tools for image classification and simulation modeling. Quantum GIS is an open-source framework that is considered an option for improving the features through plugins using python language, which is regarded as programmer-friendly nowadays. The application of quantum GIS leads to the efficient development of a systematic model to process multi-temporal images for LULC (Vivekananda et al., 2020). The study has used two add-on tools, i.e., the Dzetsaka classification tool and Modules for Land Use Change Simulations (MOLUSCE) in QGIS 2.18.10 version, to generate the land cover transformation. First, the study classified the LU/LC for the selected years through the Support Vector Machin (SVM) algorithm to identify and calculate the changes in Land Use and Land Cover of the Bangalore Metropolitan Region. The SVM technique performed Supervised classification which was carried out under 7 different sample classes i.e., settlement (built-up area), water bodies (lakes, rivers, and reservoirs), wasteland, agriculture (croplands and plantations), fallow land, forest, and others (exposed hill surface, sandbars and stone quarry area). For each sample class, 30 training samples were taken into count by demarcating polygons around selected representative sites. Each sample class was given a unique class ID and a particular shade to differentiate it from one another. The process of classification was further eased by google earth, assisting in the clear identification of each pixel. Followed by this, future expansion and transformation of land use classes were executed. Then, to perform the simulation for the years 2021, 2030, and 2050, the study has used Modules for Land Use Change Simulations (MOLUSCE). The MOLUSCE model is run over the following 6 stages:

• **Input Stage:** This stage requires setting up the initial and final SVM Classification years, which are to be weighed up and spatial variables that are to be taken as suitable parameters. This model takes the initial year as the 2001 SVM classification map and the final year as the 2011 SVM classification map. The spatial variables taken into consideration are population data, DEM, aspect map, slope map, road map, and railways map.

• **Evaluating Correlation Stage:** This stage shows the correlation between the initial input year (2001) and the final year (2011) based on the spatial variables using Karl Pearson's correlation. Besides Pearson's correlation, Crammer's coefficient and Joint information uncertainty may also be used.

• **Area Changes Stage:** This stage shows the changes in the area of LULC classes between 2001 and 2011 is, represented in sq. km, and creates a LULC change map.

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• **Transition Potential Modeling Stage:** This stage includes different methods of calculating transitional potential models such as Artificial Neural Networks (ANN), Multi-Criteria Evaluation (MCE), Weights of Evidence, and Logistics Regression. This study uses the method of Artificial Neural Networks (ANN) Multi-layer Perceptron, where it takes the input collection of raster pixels, carries sampling techniques, processes it, and provides users with a change map. It gives us a neural network learning curve based on the criteria such as the neighborhood pixel as 1, learning rate as 0.100, the maximum number of iterations done as 1000, hidden layers as 10, and momentum as 0.05 (Kamaraj and Rangarajan, 2021).

• **Cellular Automata Simulation Stage:** After the kappa value from the previous stage is in accordance with the assessment standard, then the third-year LULC change prediction process is carried out using the cellular automata simulation method (Hakim et al., 2019). This stage takes transition probabilities, calculates the count of pixels that have to be changed, and gives us the model of the 2021 map with 1 iteration.

• **Validation Stage:** The valuation of the 2021 LULC map generated is carried out with the help of the kappa coefficient. It takes the input as the predicted 2021 LULC map and the reference map as the 2021 SVM classification map. The kappa coefficient is calculated as below equation (1).

$$Kappa = \frac{p_o - p_e}{1 - p_e} \qquad (1)$$

where p_o indicates the proportion of actual agreements and p_e indicates the proportion of expected agreements.

where, $p_o = \sum_{i=1}^{c} p_{ij}$ and $p_e = \sum_{i=1}^{c} p_iT\, pT_j$, where p_{ij} is the i-th and j-th cell of a contingency table, p_iT is the sum of all cells in the i-th row, pT_j is the sum of all cells in the j-th column, c is the count of raster categories.

3. RESULTS AND DISCUSSIONS

The study has provided with the following results:

3.1 Land use and Land cover classification of 1981-2021

The study shows the total area each LULC class has occupied over the BMR region. Table 1 and figure 7 indicate how the area under different LULC classes has changed over time from 1981 to 2021. 1981 (Fig. 2) has the highest area under fallow land (47.99%), followed by agriculture (19.43%) and forest (13.97%). 1991 (Fig.3) has the highest area under fallow land (60.67%), wasteland (16.6%), and agriculture (6.02%). 2001 (Fig. 4) has the highest area under fallow land (35.75%), settlement (24.37%), and agriculture (13.61%). 2011 (Fig. 5) has the highest area under fallow land (35.71%), settlement (24.45%), and agriculture (13.61%). 2021 (Fig. 6) has the highest area under settlement (40.61%), fallow land (18.74%), and forest area (17.56%). A transition in the agricultural and settlement class can be noticed. The transition of agriculture is because of growing commercial and residential space, the construction of the upcoming metro line, the widening of National Highway 209, etc. (Varkey, 2019), while the growth of residential spaces due to high demand because of in-migration is the key driver for the increase in the area of the settlement class.

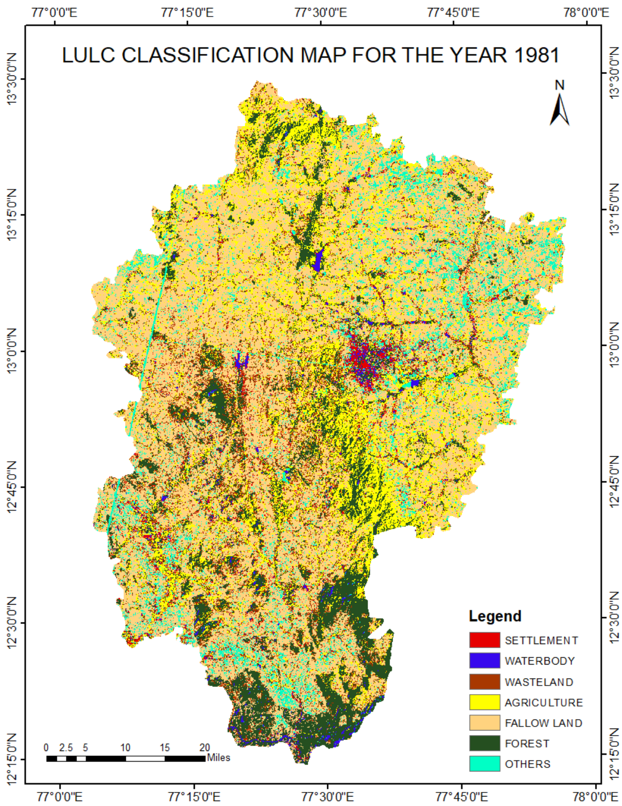

Figure 2: LULC Classes of 1981

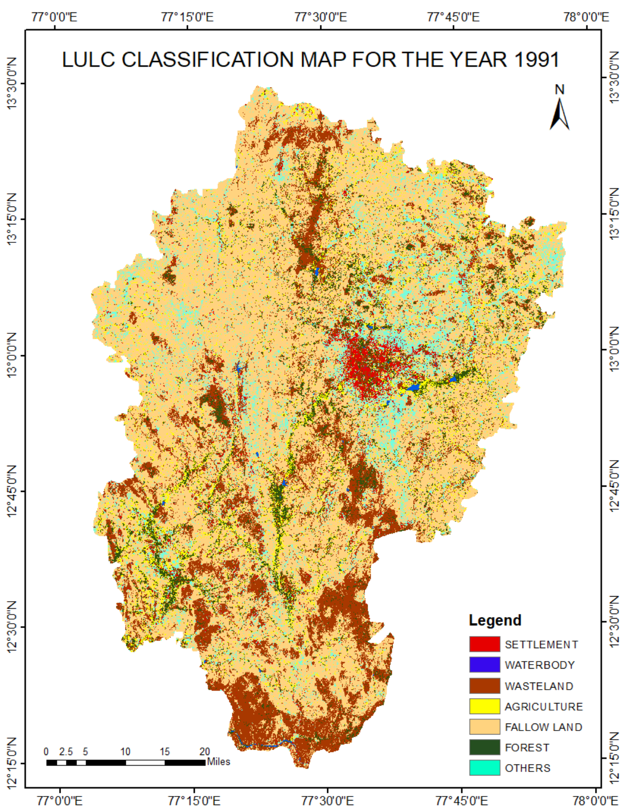

Figure 3: LULC Classes of 1991

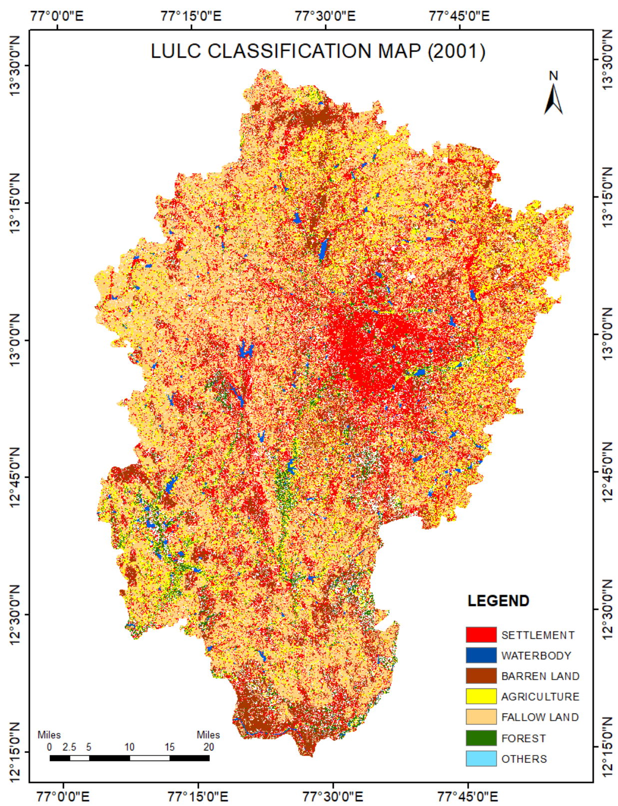

Figure 4: LULC Classes of 2001

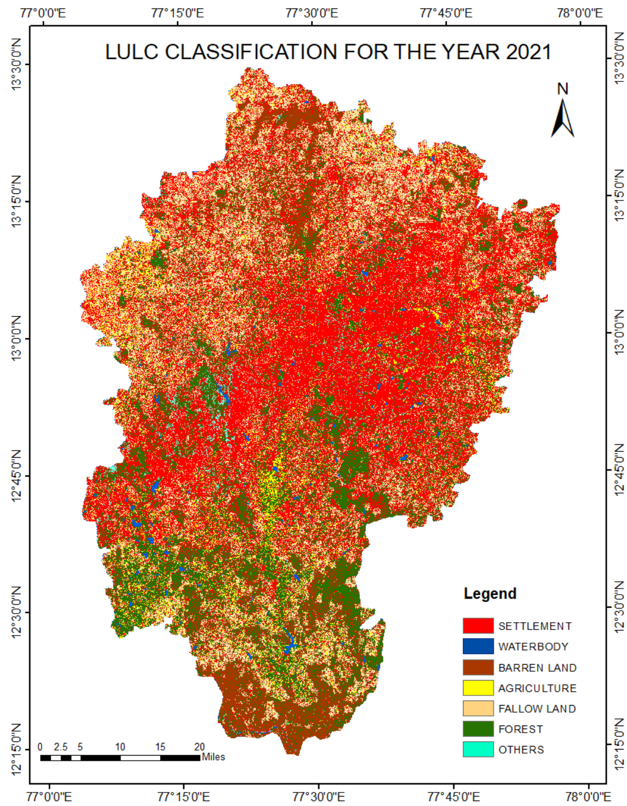

Figure 6: LULC Classes of 2021

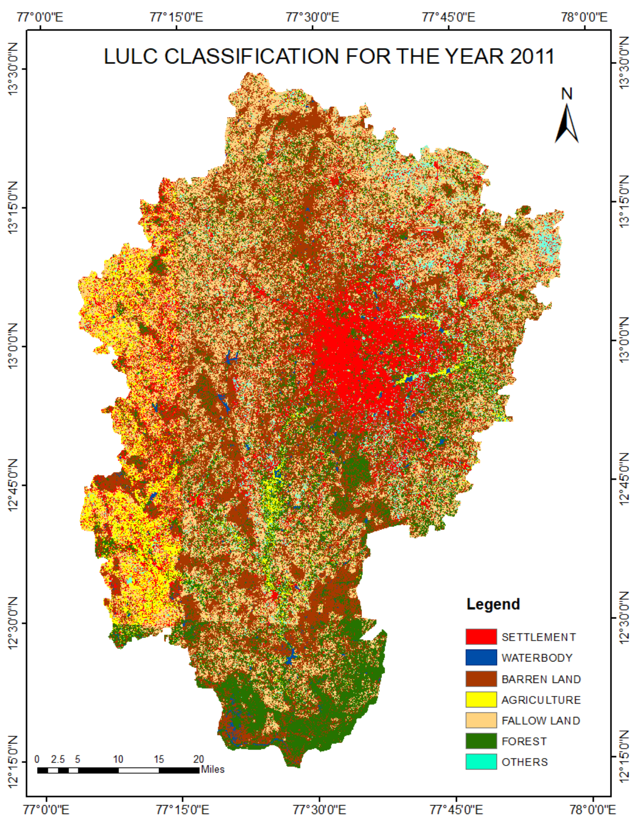

Figure 5: LULC Classes of 2011

Figure 7 clearly shows the areas under different land use classes in percentage between 1981-2050. The chart depicts less settlements development in 1981 (5.9%), whereas in 2050, it shows 59.9%, the predicted settlement expansion ten times than 1981 settlement area coverage. Similarly, wasteland areas are decreasing from 1981 (62%) to 2050 (2.5%). This shows that in future, most of the open / wasteland will be converted into settlement plots, commercial and industrial activity or other related infrastructural development activities. Also, water-bodies areas are drastically shrinking. There is a fluctuation in the agricultural areas. It increased from 2.4 % to 13.6 % (1981 - 2011) and decreased from 13.6% to 3% (2011 - 2050), which shows a declining trend in the agricultural areas.

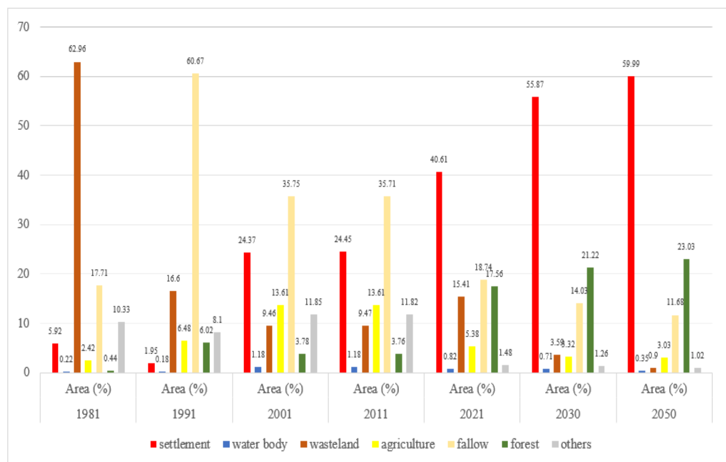

Figure 7: Area Under Different LULC Classes in Percentage

LULC Class	1981		1991		2001		2011		2021		2030		2050	
	Area (sq. km)	Area (%)	Area (sq. km)	Area (%)	Area (sq. km)	Area (%)	Area (sq. km)	Area (%)	Area (sq. km)	Area (%)	Area (sq. km)	Area (%)	Area (sq. km)	Area (%)
Settlement	174.66	**2.18**	156	1.95	1950.59	24.37	1954.95	24.45	3251	**40.61**	4472	55.87	4802.21	**59.99**
Waterbody	81.76	**1.03**	14.68	0.18	94.4	1.18	94.69	1.18	65.54	**0.82**	57	0.71	28.12	**0.35**
Wasteland	622.91	**7.78**	1328.47	16.6	757.57	9.46	758.65	9.47	1233.13	**15.41**	287	3.59	72.04	**0.9**
Agriculture	1555.76	**19.43**	518.95	6.48	1088.93	13.61	1089.78	13.61	430.45	**5.38**	266	3.32	242.22	**3.03**
Fallow	3841.75	47.99	4856.94	60.67	2861.91	35.75	2858.66	35.71	1500.32	18.74	1123	14.03	935.33	11.68
Forest	1118.52	13.97	481.98	6.02	302.85	3.78	301.58	3.76	1405.85	17.56	1699	21.22	1843.06	23.03
Others	609.64	7.62	647.98	8.1	948.75	11.85	946.69	11.82	118.71	1.48	101	1.26	82.02	1.02
Total Area	8005	100	8005	100	8005	100	8005	100	8005	100	8005	100	8005	100

Table 1: Area under different LULC classes has changed over time from 1981 to 2050.

3.2 Land use and Land cover changes in 1981-2021 and 2021-2050

Table 2 shows the percentage of area change of the LULC Classes from 1981- 2021, 2021-2050, and 1981-2050. From 1981-2021 positive changes are observed in settlement (17.61%), wasteland (0.97%), and forest (0.25%), while waterbody (-0.19%), agriculture (-0.72%), fallow land (-0.6%), and others (-0.8%) have witnessed negative changes. From 2021-2050 positive changes are being observed in settlement (0.47%) and forest (0.31%), while waterbody (-0.57%), wasteland (-0.94%), agriculture (-0.43%), fallow land (-0.37%) and others (-0.3%) have witnessed negative changes. From 1981-2050 the LULC Class has witnessed an overall change of 26.49% in the settlement, -0.65% in a waterbody, -0.88% in wasteland, -0.84% in agriculture, -0.75% in fallow land, 0.64% in a forest, and -0.86% in others.

LULC Class	1981-2011 (% Change)	2011-2050 (% Change)	1981-2050 (% Change)
Settlement	10.19	1.45	26.49
Waterbody	0.15	-0.7	-0.65
Wasteland	0.21	-0.9	-0.88
Agriculture	-0.29	-0.77	-0.84
Fallow	-0.25	-0.67	-0.75
Forest	-0.73	5.11	0.64
Others	0.55	-0.9	-0.86

Table 2: Percentage change of LULC from 1981-2050

Figures 3 to 6, 8 and 10 show the Bangalore Metropolitan Region's urban expansion pattern. Urban expansion is visible, and it is observed to be expanding in every direction, mainly in the south and southwestern direction. In the early stages, it showed an expansion in its outer fringe areas and gradually expanded more towards the southern direction. Expanding urban areas is the result of a large scale of in-migration from rural areas within the state and from other states on the grounds of higher education, better standard of living, better career opportunities and so more. Along with this Bangalore being one of the metropolitan cities in India, industrialisation also plays a vital role as a pull factor in urban expansion, as a result of which it has become the headquarters of many IT companies and home to many international immigrants as well.

3.3 Land use and Land cover predicted for 2030 and 2050

Figure 8 and 10 shows the upshots of 2030 and 2050 predicted simulation. Validation of the simulation was done using the kappa coefficient which is shown in table 3 and figure 8, which shows the reliability of the results and the data used.

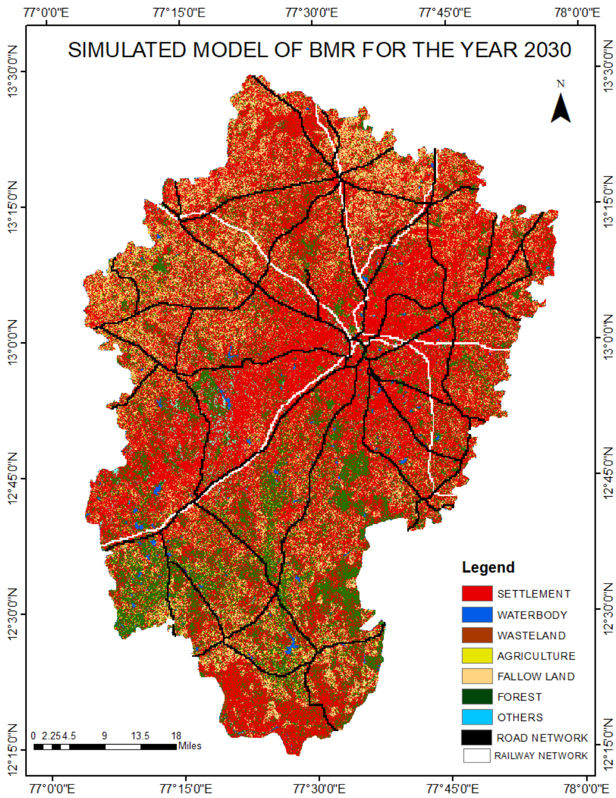

Figure 8: Predicted LuLc of 2030

KAPPA VALUE	YEAR	
	2030	2050
CRITERIA	KAPPA VALUE IN %	
Percentage of Correctness	85.58	81.56
Kappa Overall	0.8	0.74
Kappa Histogram	0.84	0.79
Kappa (Location)	0.95	0.94

Table 3: Validation using Kappa

Table 3 indicates the percentage of the correctness of the simulated 2030 and 2050 as 85.58% and 81.56%, respectively, with an overall accuracy of 0.8 and 0.7, which can be interpreted as an almost perfectly reliable simulation.

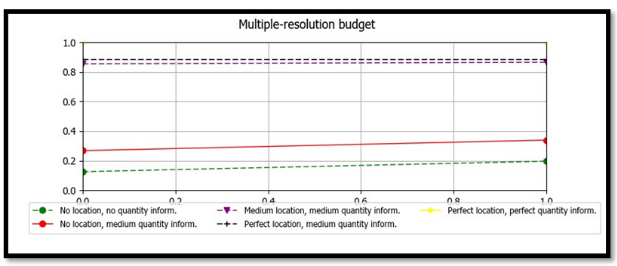

Figure 9: Validation Graph between simulated 2030 and 2050

Table 1 shows that in 2030 and 2050, the highest area is under settlement (55.87% and 59.99% respectively) accompanied by forest (21.22% and 23.03%) and fallow land (14.03% and 11.68%). Settlement class has witnessed a gradual increase in its area from 2001 onwards and is predicted to occupy the highest area shortly. The waterbody class has spotted a negative change of 0.35 % in 2050 from 1.03% in 1981.

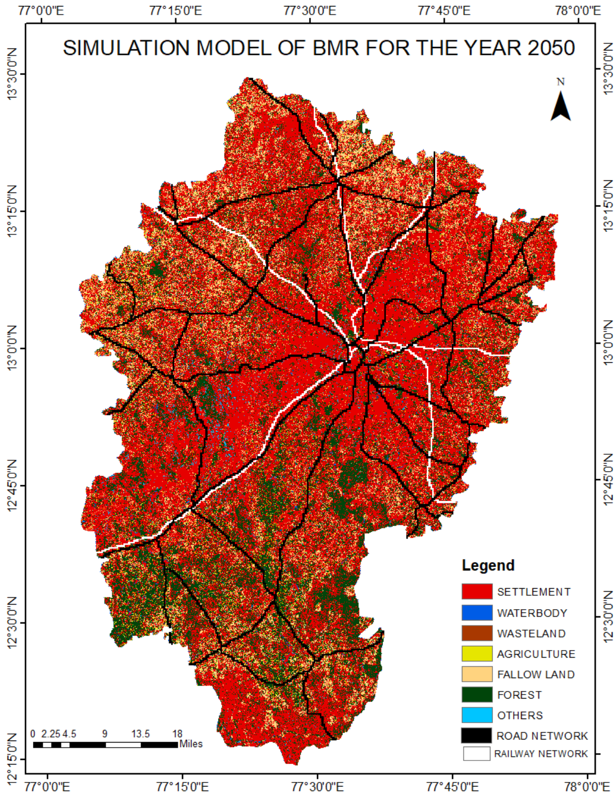

Figure 10: Predicted LuLc of 2050

The wasteland class is observed to gradually decrease in its area since 2011 (9.47%) and is predicted to decrease more by 2050 (0.9%). The agriculture class has witnessed an overall change in its area from 19.43% in 1981 to 5.38% in 2021 and is predicted to change as 3.03% in 2050. Fallow land is seen to be decreasing from 47.99% in 1981 to 18.74% in 2021 and is predicted to further decrease to 11.68% in 2050. The Forest class has witnessed an overall increase in its area from 13.97% in 1981 to 17.56% in 2021 and is predicted to increase to 23.03% in 2050.

The simulation model presents the future perspective of the Bangalore Metropolitan Region, indicating population growth and urban expansion in the fringe areas. Urban expansion shortly is predicted to cover up most of the wasteland areas in the southern parts of the BMR and is expected to expand more in the future. Infrastructure development plays a crucial role in urban expansion but poor infrastructure facilities in the BMR may create difficulties in managing the expansion. This study shows the possible areas of expansion which can help manage the expansion and develop the infrastructure facilities.

3.4 Normalised Built-up index

The NDBI value ranges from -1 to 1. The study gives NDBI for the years 2001, 2011, and 2021 (Fig. 11). The NDBI value for the year 2001 ranges between -0.7 to 0.6, for 2011 the value ranges from -0.55 to 0.26, and for 2021 it ranges from -0.2 to 0.9. The higher and positive values highlight the built-up areas and the negative values indicate the water bodies. However, the Lower NDBI value represents vegetation. For all three years the high built-up areas are mostly concentrated in the Bangalore urban region with some clusters of concentration near satellite towns of the fringe areas towards the year 2021. The NDBI for all three years particularly accentuates the built-up areas and makes the analysis of the study uncomplicated.

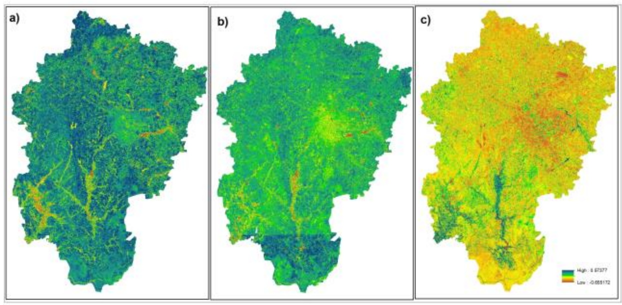

Figure 11: BMR Built up index of a) 2001 b) 2011 c) 2021

3.5 Impact of Urban Expansion

The simulated lulc (2030 & 2050) predicts how the urban expansion will be taking place shortly. The maps indicated that the urban expansion may lead to a reduction in the area occupied by other LULC classes such as agriculture, waterbody, and wasteland. Waterbody and agriculture classes are seen to be dropping off in its area, expressing the probability due to urban expansion. Apart from reducing LULC class area, urban expansion may also affect transportation networks, traffic congestion, and other communication lines. It may also lead to congested built-up areas and affect the infrastructure utilities in the Bangalore Metropolitan Region.

4. CONCLUSION

The core upshots of this technique show the land use and land cover transformation and urban expansion pattern in the Bangalore Metropolitan Region. It also illustrates the Spatial-temporal changes and how dispersion or expansion has occurred in the last five decades and project future three decades. This study reveals that land use and land cover changes are faster and more rapid transformation, especially in the fringe areas, due to the less availability and high cost of land value in the core areas. This could be monitored and make an appropriate smart urban plan to be implemented. The results are expected to aid society and several organisations such as city planners and policymakers. The results will assist the policymakers to make policies to control the issues of population expansion and related concerns. It will also be of great use to the city planners in tackling the issues such as traffic congestion, encroachment, and so on. Overall, this study will help plan for management strategies for a sustainable urban environment.

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