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Environmental Consequences in the Neighbourhood of Rapid Unplanned Urbanisation in Bangalore City

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Abstract

The knowledge of landscape dynamics aids in evolving strategies for the prudent management of natural resources to sustain ecosystem services. The availability of spatiotemporal remote sensing data with advancements in artificial intelligence (AI) and machine learning (ML) algorithms has aided in assessing the ecological status in urban environments, markedly revealing complex patterns and interactions. The current communication presents landscape dynamics in the Bengaluru Urban district from 1973 to 2022 using a supervised machine learning technique based on the Random Forest algorithm with temporal Landsat data, which showed a 51.86% increase in the built-up area and a 26.28% decrease in the green cover. Rapid unplanned urbanization after globalization and the opening up of Indian markets (in

Bengaluru city) has witnessed erosion in the natural surface (waterbodies and green cover) in the neighborhood, which has been impacting the health of the environment and people. Computation of fragmentation indices showed a decline of the native green cover by 177.2 sq. km. in the southern part of the district. Likely land use changes are predicted using the Cellular Automata Markov model considering the base case scenario. The analyses revealed a further possible increase in built-up to 1536.08 sq. km, a decrease in green cover by 14.32 sq. km by 2038, and the disappearance of water bodies, which highlights the need to mitigate the adverse impacts of land use changes through planned urbanization considering the environment and livelihood of local communities. The decline of heat sinks such as water bodies and green cover would contribute to an increase in the land surface temperature (LST), which would affect the microclimate of Bengaluru, highlighting the need to sustain ecosystem services to support the livelihood of local communities. Understanding the ecological significance of diverse habitat characteristics of the urban region and the prediction of likely changes in a high degree of spatial heterogeneity would assist the decision-makers in framing appropriate policies.

Keywords

Urbanization; land use and land cover (LULC); machine learning; landscape modelling; fragmentation analysis

1. Introduction

Landscape comprises heterogeneous interacting ecosystem elements with diverse ecological, biological, geological, hydrological, social, economic, and environmental characteristics [1]. The structure of a landscape decides the functional capabilities reflected through bio-geo-socio-economic variables and the resources associated with them [2]. Assessment of landscape dynamics aids in understanding the structure through insights into the spatial pattern and change trend associated with the landscape [3]. Insights into landscape dynamics are crucial for the sustainable management and security of natural resources [4]. Landscape dynamics have been evaluated using temporal-spatial data (remote sensing data) through land cover (LC) and land use quantifications, which help evolve natural resources management policies [5, 6]. Quantitative analyses of land use and land cover would aid in ascertaining alterations in landscape spatial patterns [7] due to anthropogenic activities and natural processes.

Unplanned economic and industrial activities leading to rapid urbanization, industrialization, infrastructure development, and consequent population increase have been eroding green natural resources of forest cover, water bodies, and agricultural lands [8]. Rapid land use changes are dynamic and unsustainable, making it essential to analyze quantitative changes in spatial patterns of landscape dynamics [9] to plan interventions for mitigating impacts on ecosystems, including alterations in climate patterns, hydrologic and bio-geochemical cycles, affecting the livelihood of people [10, 11]. Land use and land cover information are derived accurately using temporal remote sensing data through machine learning techniques of the Random Forest (RF) classifier [12], which is an ensemble-based Machine Learning (ML) algorithm incorporating bagging and boosting techniques [13]. RF is a non-parametric technique that generates a set of decision trees from a randomly selected subset of the training set and consolidates their decisions to determine the final class.

Forest ecosystems are crucial in maintaining ecological balance and supporting economic development [14]. However, unplanned developmental activities leading to land degradation and deforestation have increased land surface temperatures [15], and the process was accentuated after globalization in the 1990s, causing large-scale forest land transitions [16]. LULC changes alter the structure of the landscape, inducing fragmentation of contiguous forests into smaller patches, which is detrimental to the sustenance of biodiversity, carbon sequestration potential, and other ecological services at local and global scales [17].

Modeling and geo-visualization help visualize likely land cover transitions in advance and hence emerged as indispensable tools to ensure effective landscape management [18]. The endeavor helps identify areas likely to undergo changes, which helps in understanding potential environmental impacts [19-22].

Insights of land use dynamics with bio, geo, climatic, ecological, and social parameters aided in delineating ecologically sensitive zones, with inherent spatial patterns of land use for prudent management to sustain natural resources [23] and serve as spatial decision support systems for regional planners and decision-makers, These tools provide empirical interpretations of spatial transformations, which helps to recommend strategies that are essential for landscape conservation through protection of fragile ecosystems and mitigation of ecological impacts [24]. There have been significant efforts to understand urban dynamics using temporal and spatial data acquired at regular intervals since the 1970s through space-borne sensors (Remote sensing data). Most of the studies assessed urban growth and sprawl [4, 7-11, 14-16, 18-36], but the information on the environmental impacts of rapid urbanization is scanty. In this context, the novelty of the research is to assess the environmental impacts of the rapidly urbanizing landscape using spatial big data through machine learning algorithms, which aided in assessing the extent of urbanization and condition of ecosystems (through fragmentation of forests) and geo-visualizing likely land use changes in the neighborhood with the current path of rapid urbanization.

Understanding landscape dynamics is crucial for achieving sustainable land resource management with information on spatiotemporal alterations in land use and land cover. Modeling and geo-visualization of landscape dynamics are essential for effective landscape management as they help identify areas likely to undergo changes and delineate ecologically sensitive zones for regional planning. A comprehensive understanding of the quantitative changes in spatial patterns and their impacts on ecosystems and people's livelihoods is necessary to plan interventions for mitigating the adverse effects. Objectives of the current research are [i] to analyze temporal-spatial data quantitatively to understand land use and land cover dynamics from 1973 to 2022, [ii] to assess the condition of forests through fragmentation metrics, and [iii] to predict/geo-visualize likely land use changes in the neighborhood with the current path of rapid urbanization through land use modeling.

2. Materials and Methods

2.1 Study Area: Bangalore Urban District, Karnataka State, India

Bangalore Urban district (Figure 1) is situated at 12°39’32” and 13°14’13” N and 77°19’44” and 77°50’13” E in the southeastern part of Karnataka with a total area of 2201 sq. km. The district is divided into 3 Taluks: Bangalore North, Bangalore South, and Anekal. The hilly terrain of the Anekal range in the southern part of Bangalore urban district is home to the Bannerghatta National Park, which covers an area of 260.51 sq. km and is situated approximately 22 km south of Bangalore. The National Park, with an elevation ranging from 1245-1634 m, has moist deciduous forests in the valley and scrubland in higher elevated regions [37].

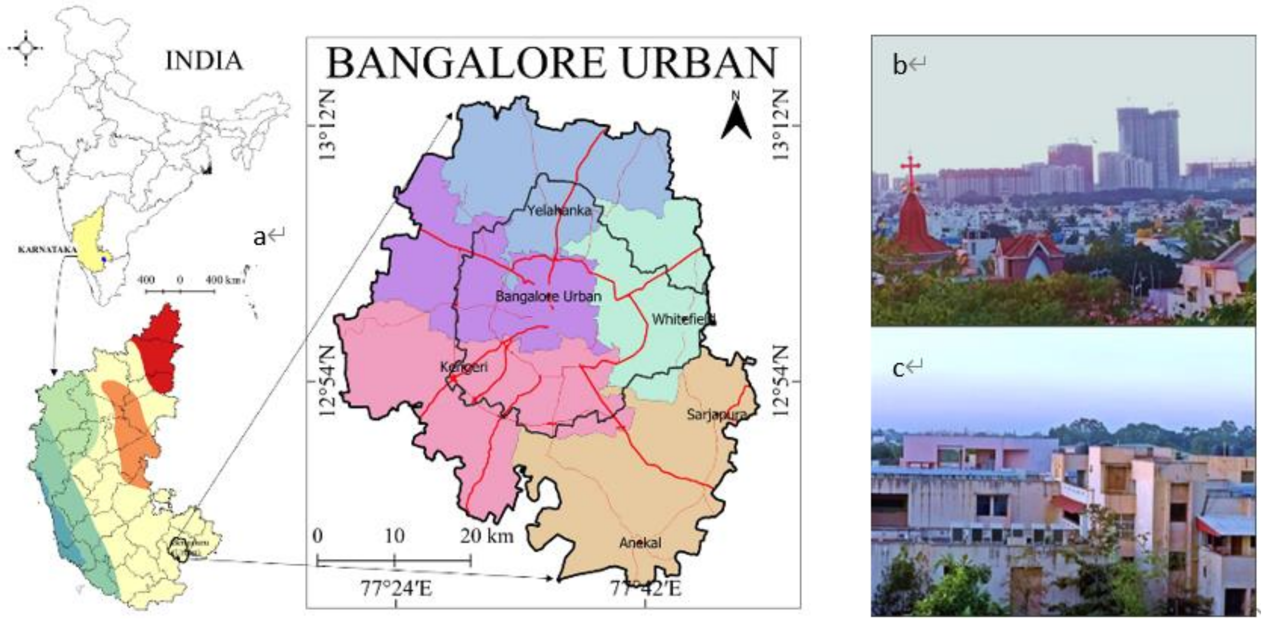


Figure 1 (a) Location of Bangalore Urban district (with administrative divisions), Karnataka State, India; (b) Dense Urban area in core Bangalore city; and (c) Sprawl in peri-urban regions (Source: Author).

Bangalore urban district experiences a typical monsoonal climate, with the southwest monsoon contributing to a significant portion of the rainfall. Pre-humid to semi-arid climatic conditions can be observed in the district, with an average temperature of 23.1°C. The Cauvery River drains most of the district. In terms of physiography, the district comprises rocky upland, plateau, and flat-topped hills with an elevation of approximately 900 m above mean sea level. The region is undulating, with mostly slopes towards the south and southeast, forming pedi-plains interspersed with hills throughout the western part. The district is mainly covered with red loamy soil and lateritic soil [28].

Bangalore urban district is located in the eastern dry zone, the agroclimatic area. The district accounts for 70% of rose exports from India and is a hub for floriculture industries. Most Micro, Small, and Medium enterprises (MSME) (around 10%) are engaged in Agro and Food Processing. As per the 2011 Census, Bangalore district is the most populous district in Karnataka, with a total population of 96,21,551 and the highest population density of 4,381 per sq. km. It also has the highest decadal growth rate of 47.2% in the state. The district is predominantly urbanized, with 90.9%

of the population residing in urban areas, and boasts a literacy rate of 87.7%, the second-highest in the state. Additionally, the district's Gross District Domestic Product (GDDP) was estimated to be Rs. 99,325 Crore during 2012-13, contributing 33.30% to the state's economy. The district's average per capita annual income, according to the report of the Economic Survey of Karnataka (2022–23), is Rs. 621131 [38, 39]. This district is the main administrative center of Karnataka, with the municipality Bruhat Bangalore Mahanagara Palike (BBMP) located at the center of the district. The landscape is predominantly urban (built-up or paved surfaces), with agricultural and horticultural lands in the peri-urban areas [28].

2.2 Data

Spatial data with spectral and spatial resolutions used for assessing landscape dynamics are listed in Table 1.

Table 1 Spatial data used for the study.

Data and source	Bands	Spatial Resolution	Purpose
Landsat Multispectral Scanner (MSS) US Geological Survey https://earthexplorer.usgs.gov/	B6, B5, B4	60 m	LULC analysis
Landsat Thematic Mapper (TM) US Geological Survey https://earthexplorer.usgs.gov/	B2, B3, B4, B5, B6, B7	30 m	LULC analysis
Landsat Operational Land Imager (OLI) US Geological Survey https://earthexplorer.usgs.gov/	B2, B3, B4, B5, B6, B7	30 m	LULC analysis
Vegetation map of South India (1986) by D. De Franceschi, B.R. Ramesh and J.-P. Pascal Institut Français de Pondichéry [40]	-	1:250000	Forest cover mapping
Bhuvan LULC data https://bhuvan.nrsc.gov.in/home/index.php	-	1:50000	LULC referencing
SRTM DEM US Geological Survey https://earthexplorer.usgs.gov/	-	-	Hydrology and elevation

2.3 Method

Land cover analyses: Temporal Landsat data from 1973 to 2022 have been analyzed for landscape dynamics through the Normalized Difference Vegetation Index (NDVI) to comprehend the proportion of areas covered by vegetation and non-vegetation [3, 7, 11, 15, 18, 24, 29, 35].

Land use analyses: Temporal remote sensing data were classified through a machine learning-based supervised classifier based on the Random Forest (RF) algorithm, which was chosen based on the recent work assessing the relative performance of machine learning algorithms (Random Forest (RF), Support Vector Machine (SVM), and Maximum Likelihood classifier (MLC)) for land use classification, and RF performed better with higher overall accuracy and Kappa statistics [35]. Random Forest classifier [12] is the most widely used ML algorithm based on ensemble methods like bagging and boosting [13]. RF, as presented in Figure 2, uses a set of decision trees selected randomly from the training set to aggregate decisions for determining the final class and provides a higher level of accuracy for land use classification in a diverse landscape. Training polygons corresponding to heterogenous patches in FCC were digitized, covering all categories, which are uniformly distributed and cover 15% of the study region. Attribute information for these polygons were collected from (i) the field using a pre-calibrated Global Positioning System (GPS) and (ii) online portals - Google Earth (https://earth.google.com) and Bhuvan (https://bhuvan.nrsc.gov.in). 70% of the training data were used for classification, and the remaining were used for accuracy assessment. The classifier's accuracy is evaluated through kappa statistics, which provide impartial error estimates. RF is implemented through the online cloud utility Google Earth Engine [https://earthengine.google.com/]. Spatial statistics of land uses were generated using QGIS [https://www.qgis.org/] and GRASS [https://wgbis.ces.iisc.ac.in/grass/]. Figure 3 summarises methods adopted for the analyses of land cover, and Figure 4 summarises the method adopted for land use modeling.

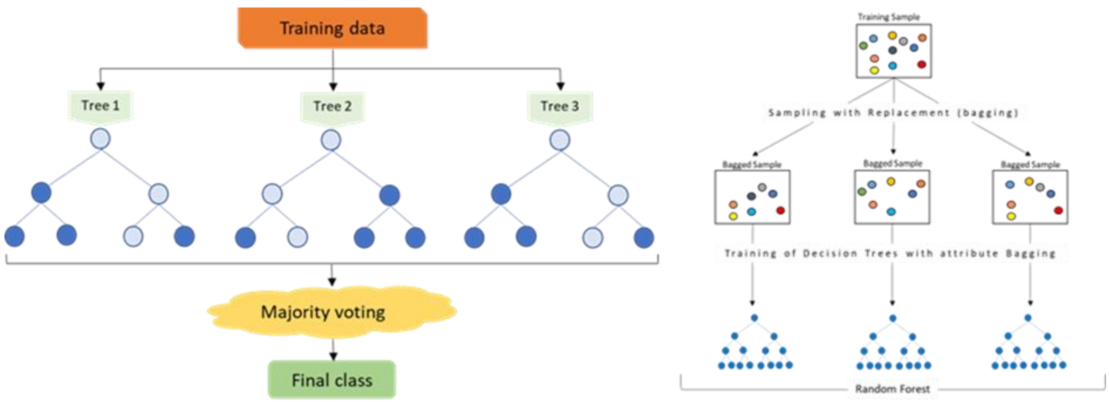


Figure 2 Random Forest classifier (Source: Author, 42).

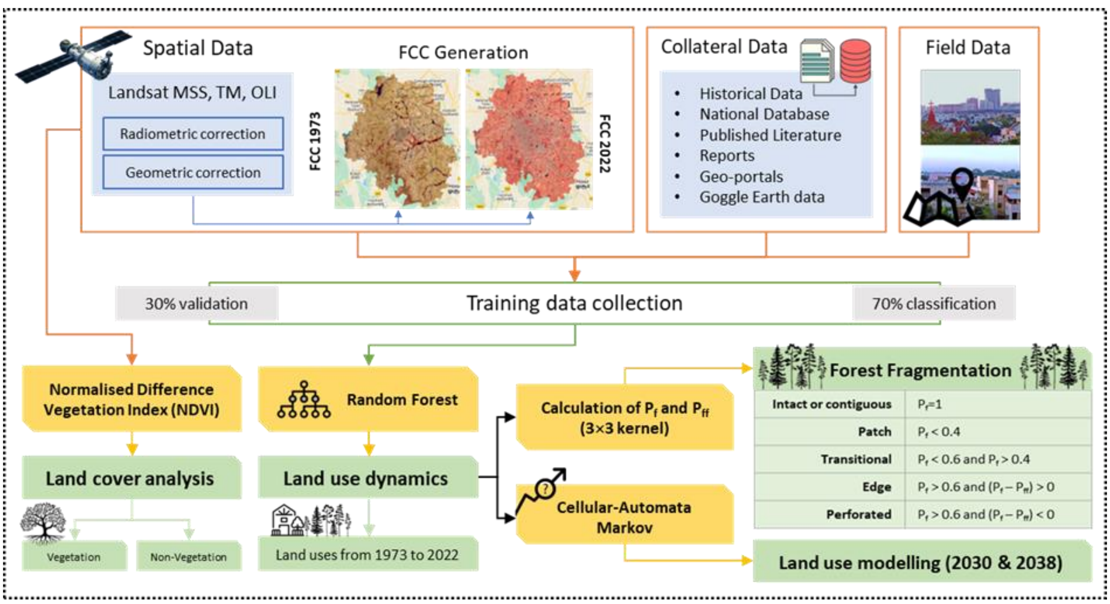


Figure 3 Schematic representation of the method for the analysis (Source: Author).

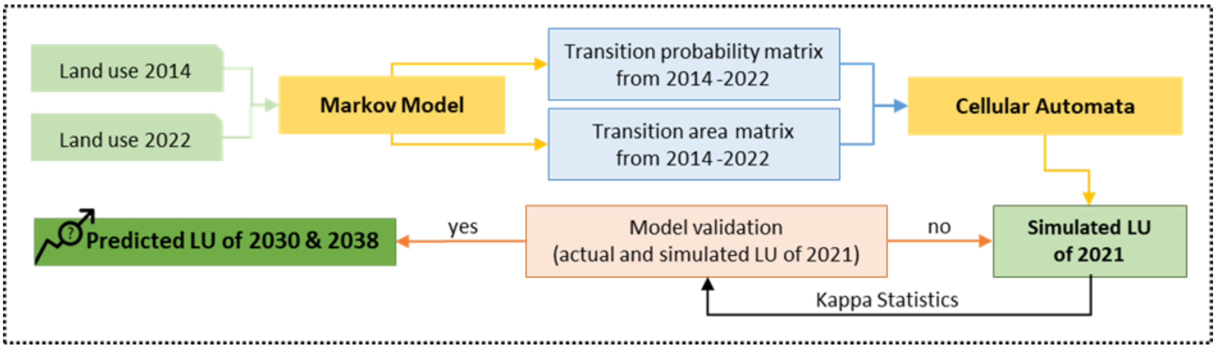


Figure 4 Method for modeling the likely land-use scenario (Source: Author).

Validation of land use classification: Validation of land use information was done through computation of overall accuracies and kappa statistics considering field data (for the latest period) and collateral data (published literature).

Assessment of conditions of forests through forest fragmentation metrics using GRASS [https://wgbis.ces.iisc.ac.in/grass/]: Using 3 × 3 kernel, fragmentation metrics P_f (the proportion of forest pixels to the total non-water pixels) and P_{ff} (ratio of the number of forest pixel pairs to the total number of adjacent pairs of at least a forest pixel in the cardinal direction) were computed iteratively for the entire study region to understand the condition of forest ecosystems (Figure 3). Based on P_f and P_{ff}, pixels are categorized as intact or contiguous ($P_f = 1$), patch ($P_f < 0.4$), transitional ($P_f < 0.6$ and $P_f > 0.4$), edge ($P_f > 0.6$ and (P_f-P_{ff}) > 0), perforated ($P_f > 0.6$ and ($P_f - P_{ff}$) < 0) and non-forest (contain anthropogenic land uses) pixels [4, 17].

Land use modeling: Cellular Automata Markov model is implemented to visualize likely land uses (Figure 4) using IDRISI software [https://clarklabs.org/] to simulate the potential land use in 2030 and 2038. Integrated CA-Markov [18-22] is significant as it can accurately simulate and predict future conditions by its dynamic explicit simulation efficiency.

The transition probability spatial information is obtained based on the Markov process. The future state of change (S_{t+1}, probable land use at time t + 1) is calculated as the product of S_t (land use at time t) and transition probability P_{ij} [18-22].

Cellular Automata [18, 20] is used to simulate and predict future LU based on transition potential (equation 1). The CA model consists of state, cell and cell space, neighborhood, rule, and time, and in the case of land use transformation, the cell represents the cells of the LULC class, and the class represents itself as a state. A discrete dynamic function of CA consists of four elements expressed by the following formula.

$$CA = (l, \Sigma, \eta, \delta) \tag{1}$$

Where, l = physical environment and discrete lattice, Σ = the set of possible states, η = the neighborhood of a cellular automaton, δ = local transition rule.

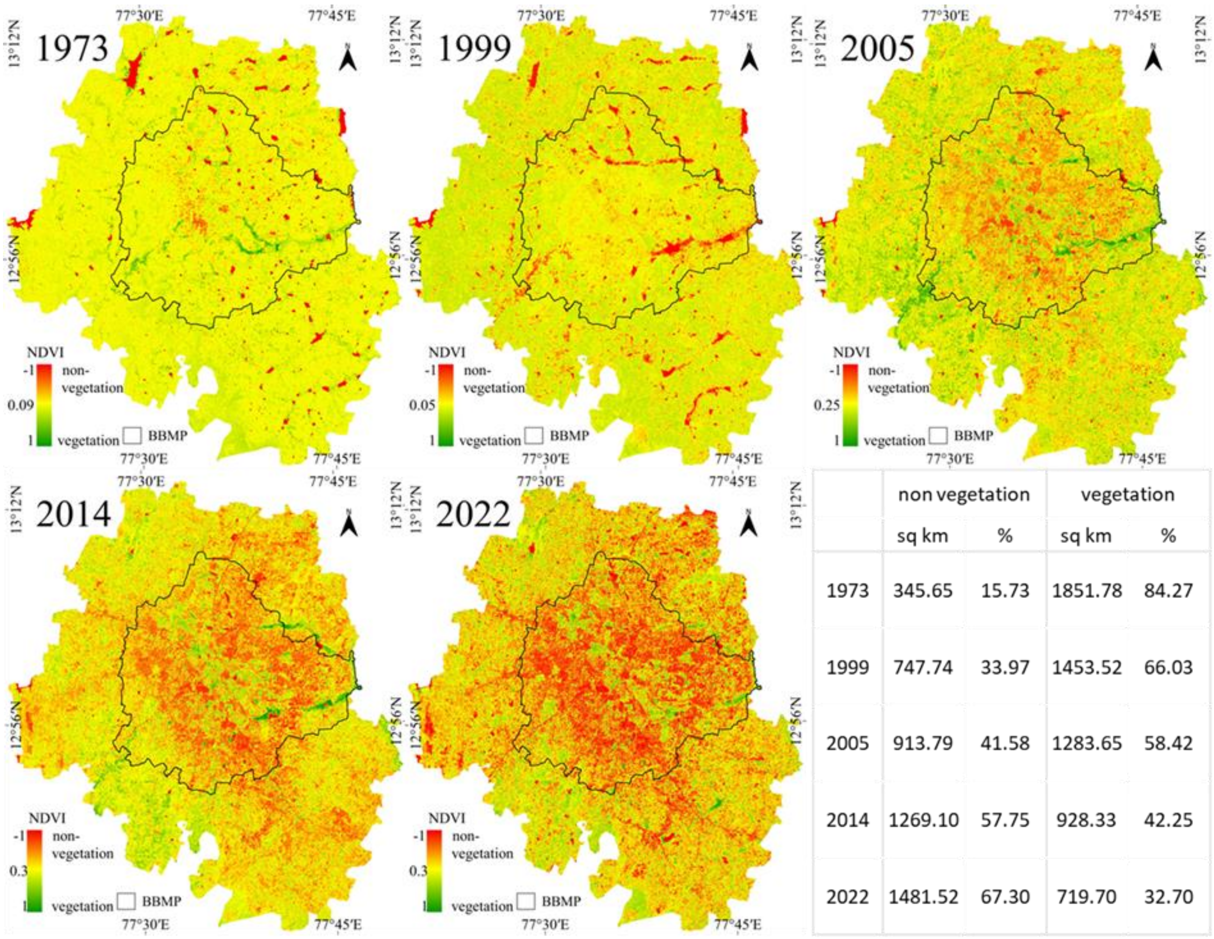
Von Neumann's 5 × 5 filter was used for modeling, and waterbodies were considered a constraint for simulation. Validation was carried out by comparing simulated land uses with actual land uses through Kappa Statistics. Higher accuracy was achieved through calibration by fine-tuning the input variables. A validated model was then used in the business-as-usual scenario to predict and visualize likely land uses in 2030 and 2038.

3. Results

Land use and land cover (LULC) assessment was done considering the availability of cloud-free data, which were available for the period 1973, 1999, 2005, 2014, and 2022. Analysis of Landsat data of 1973 provided LULC during the pre-globalization period. Globalization and the opening of Indian markets started in 1990 and gained momentum in the mid-1990s. Hence, Landsat TM of 1999 and 2005 were used to understand LULC dynamics, while Landsat OLI data of 2014 and 2022 aided in understanding the urban dynamics during the latest decade.

3.1 Land Cover

Bangalore urban district was rich in agricultural resources in the 1970s. Post-liberalization from 1990 onwards, with the spurt in developmental activities, contributed to rapid urbanization with urban sprawl, leading to a decrease in agricultural lands in this district, enhancing carbon content in the atmosphere [41]. As agricultural lands, fallow land, and open spaces were converted into urban spaces, the area under non-vegetation is seen to increase from 15.73% to 67.3% from 1973 to 2022 (Figure 5).



	non vegetation		vegetation	
	sq km	%	sq km	%
1973	345.65	15.73	1851.78	84.27
1999	747.74	33.97	1453.52	66.03
2005	913.79	41.58	1283.65	58.42
2014	1269.10	57.75	928.33	42.25
2022	1481.52	67.30	719.70	32.70

Figure 5 Land cover Analysis of Bangalore Urban district from 1973 to 2022 (Source: Author).

3.2 Land Use

Land use analyses (Figure 6, Table 2) showed that this district's area under built-up has increased drastically during the last five decades. Bangalore was spatially expanded in the mid-2000s with the formation of the BBMP area by including rural landscapes, which led to the conversion of agricultural land to paved areas.

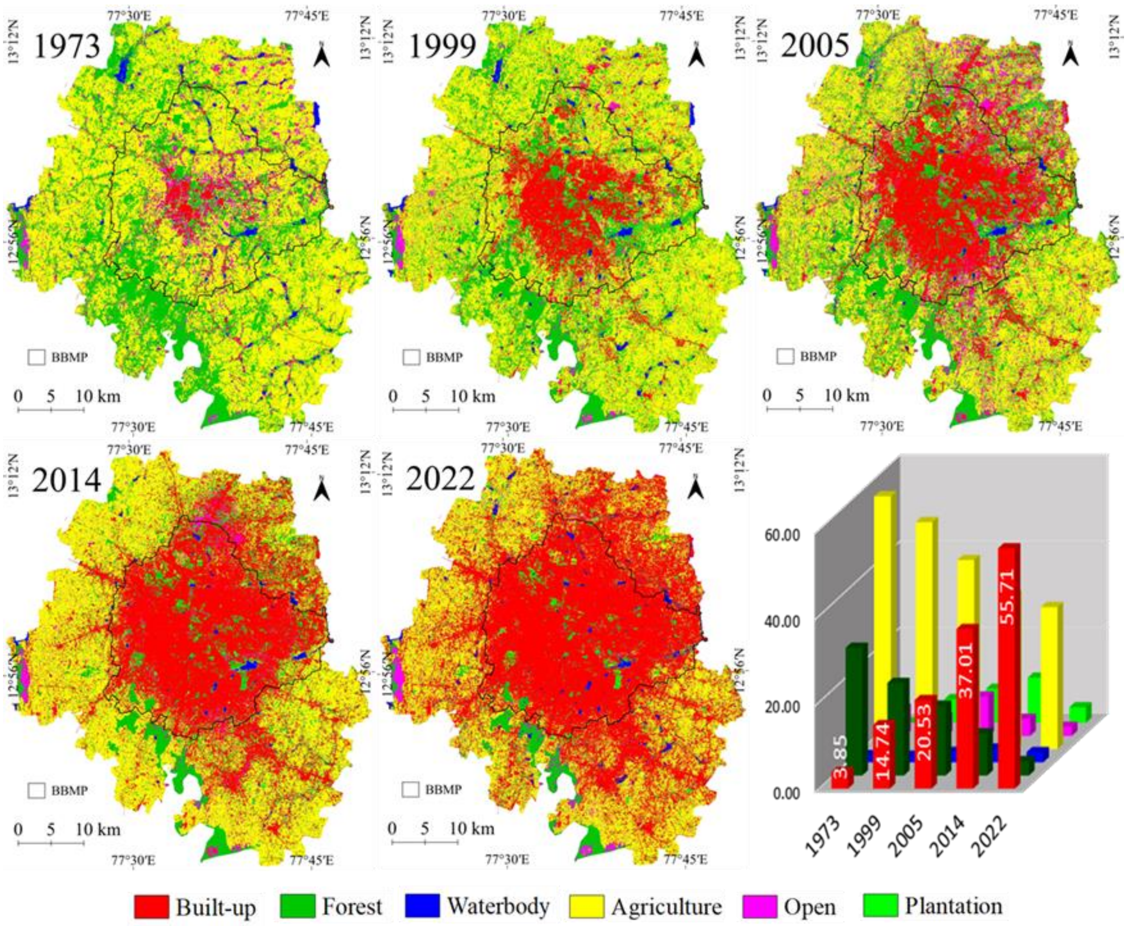


Figure 6 Land use Analysis of Bangalore Urban District from 1973 to 2022 (Source: Author).

Table 2 Land use dynamics in Bangalore Urban district from 1973 to 2022.

		1973	1999	2005	2014	2022
Built-up	sq. km	84.66	323.94	451.23	813.31	1224.27
	%	3.85	14.74	20.53	37.01	55.71
Forest	sq. km	650.61	470.89	355.94	214.59	72.97
	%	29.60	21.43	16.20	9.76	3.32
Waterbody	sq. km	36.46	32.84	52.90	70.48	52.19
	%	1.66	1.49	2.41	3.21	2.38
Agriculture	sq. km	1287.60	1156.02	963.25	782.93	723.24
	%	58.59	52.60	43.83	35.63	32.91
Open	sq. km	137.09	93.66	201.15	86.87	45.93

	%	6.24	4.26	9.15	3.95	2.09
Plantation	sq. km	1.22	120.30	173.19	229.48	79.03
	%	0.06	5.47	7.88	10.44	3.60

3.2.1 Landscape Dynamics Change in Bangalore Urban District

The spatial analyses of urban dynamics highlight alterations in the landscape structure, evident from the decline of open spaces (6.24% in 1973, which decreased to 2.09% in 2022), agricultural areas (58.59% in 1973 to 32.9% in 2022), forests (29.6% to 3.32%) and fragmentation of contiguous forests (Figure 6, Table 2). In 1973, the district had a 3.85% built-up area, which increased to 55.71% in 2022 (Figure 6, Table 2). The agricultural lands were also converted into paved areas in the last five decades, which caused a decline of areas under agricultural lands from 58.59% in 1973 to 32.9% in 2022. The peri-urban areas are becoming dense urban clusters with poor infrastructure and devoid of connectivity. The area under open spaces declined due to the conversion of open spaces into paved areas and newly formed layouts. There was 6.24% (137.09 sq. km) of open spaces in 1973, which decreased to 2.09% (45.93 sq. km) in 2022. The lakes of Bangalore urban district have been degraded due to pollution and encroachment. Some of the lakes, like Varthur Lake and Belandur Lake, are being recently rejuvenated, and currently, in 2022, 2.38% (52.19 sq. km) of the district is under water bodies. The forest areas in the outer regions of BBMP have decreased from 29.6% to 3.32% from 1973 to 2022, including the Bannerghatta National Park. The forest department has been promoting unscientific monoculture plantations of Eucalyptus, Teak, etc., in the district. It covered 0.06% in 1973, and in 2022, there is 3.6% of the area covered by plantations.

The accuracy assessment for each land use class based on the validation data showed high precision. The overall accuracy and Kappa coefficient of ladn use classification were 99.84% and 0.9967, respectively (Table 3).

Table 3 Accuracy assessment (2022).

		REFERENCE									Column total	User Accuracy
		Urban	Vegetation	Waterbody	Agriculture	Open	Wetland	Park	Horticulture	Plantation		
CLASSIFIED	Urban	3741	0	0	3	4	0	0	0	1	3749	0.9979
	Vegetation	0	31	0	0	0	0	0	0	0	31	1.0000
	Waterbody	0	0	50	0	0	0	0	0	0	50	1.0000
	Agriculture	0	0	0	666	0	0	0	0	0	666	1.0000
	Open	0	0	0	0	207	0	0	0	0	207	1.0000
	Wetland	0	0	0	0	0	187	0	0	0	187	1.0000
	Park	0	0	0	0	0	0	224	0	0	224	1.0000
	Horticulture	0	0	0	0	0	0	0	14	0	14	1.0000
	Plantation	0	0	0	0	0	0	0	0	135	135	1.0000
Row total		3741	31	50	669	211	187	224	14	136	Overall accuracy 99.84%	
Producer Accuracy		1.0000	1.0000	1.0000	0.9955	0.9810	1.0000	1.0000	1.0000	0.9926	Kappa statistic 0.9967	

3.2.2 Landscape Dynamics in the Neighbourhood of Rapidly Urbanising Landscape

Changes in land uses in the neighborhood of Bangalore city (rapidly urbanizing landscape) are presented in Figure 7 and Table 4, which shows an increase in built-up area from 1.84% (1973) to 40.91% (2022) due to urban sprawl. This has decreased forest cover from 30.21% (1973) to 4.44% (2022). A decline in agricultural land from 61.94% (1973) to 46% (2022) can be seen due to the conversion of agricultural land into paved surfaces. Spatial analyses using temporal remote sensing data, due to good rainfall during the past decade, show an increase in the spatial extent of water spread areas in the region apart from water stagnation in some mining pits (mining was rampant in the peri-urban areas to cater to the growing demand of construction materials in the rapidly urbanizing landscape (Bangalore city).

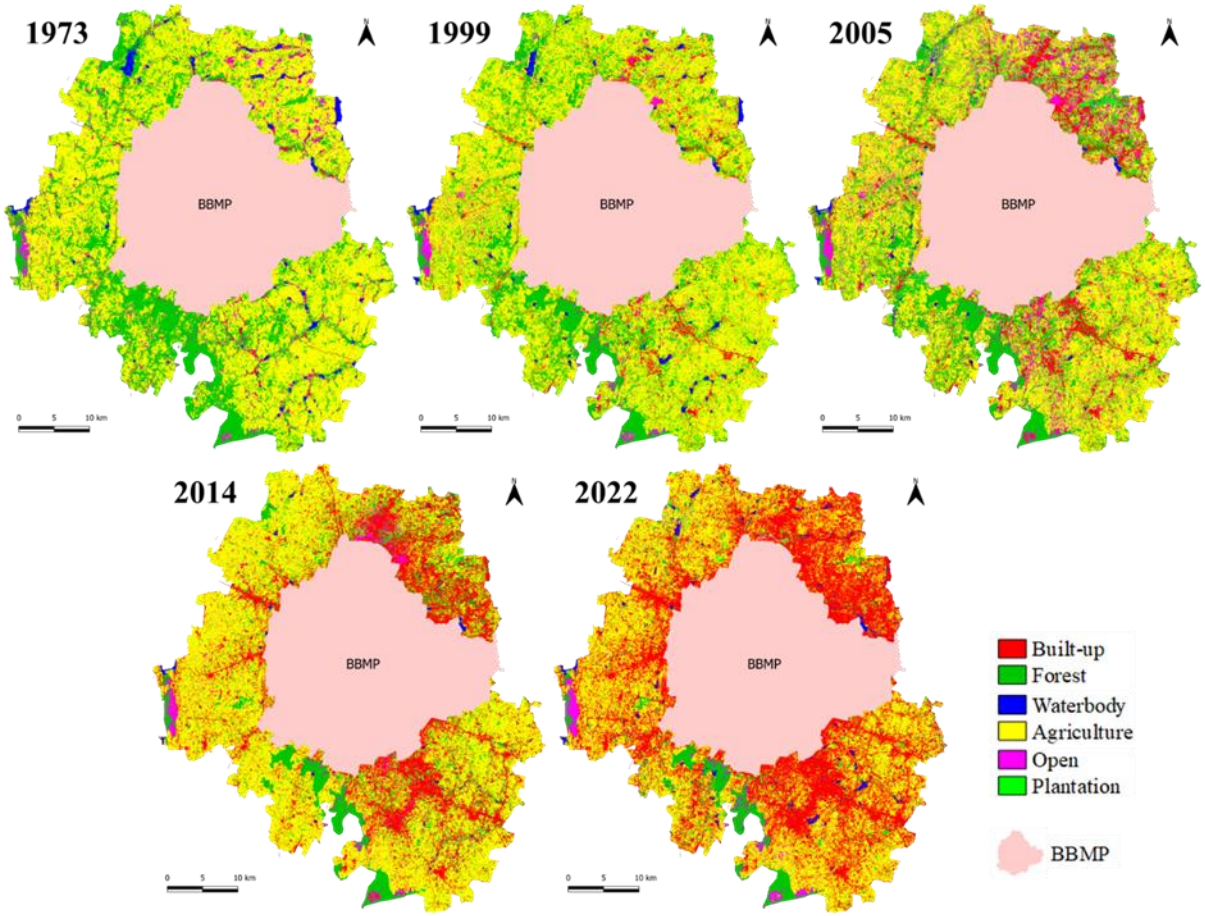


Figure 7 Land use dynamics in the neighborhood of the rapidly urbanizing landscape of Bangalore city.

Table 4 Change in land use categories in the neighbourhood of the rapidly urbanizing landscape of Bangalore city.

BBMP Surroundings		1973	1999	2005	2014	2022
Built-up	sq. km	27.39	71.32	106.09	319.43	608.03
	%	1.84	4.80	7.14	21.49	40.91
Forest	sq. km	448.97	329.63	252.83	152.93	66.01

	%	30.21	22.18	17.01	10.29	4.44
Waterbody	sq. km	23.45	21.80	37.77	56.81	37.32
	%	1.58	1.47	2.54	3.82	2.51
Agriculture	sq. km	920.53	917.61	824.11	735.02	683.70
	%	61.94	61.74	55.45	49.45	46.00
Open	sq. km	65.33	66.58	144.74	67.71	42.35
	%	4.40	4.48	9.74	4.56	2.85
Plantation	sq. km	0.58	79.31	120.71	154.35	48.84
	%	0.04	5.34	8.12	10.39	3.29

The analyses of land use dynamics of Bangalore city (BBMP) from 1973 to 2022 presented in Figure 8 and Table 5 show congestion with an exponential increase of built-up area at the cost of areas under forests, open spaces, and agricultural land. In 1973, there was 28.34% forest and 8.05% built-up area in the region, which converted into 0.98% forest and 86.63% built-up in 2022.

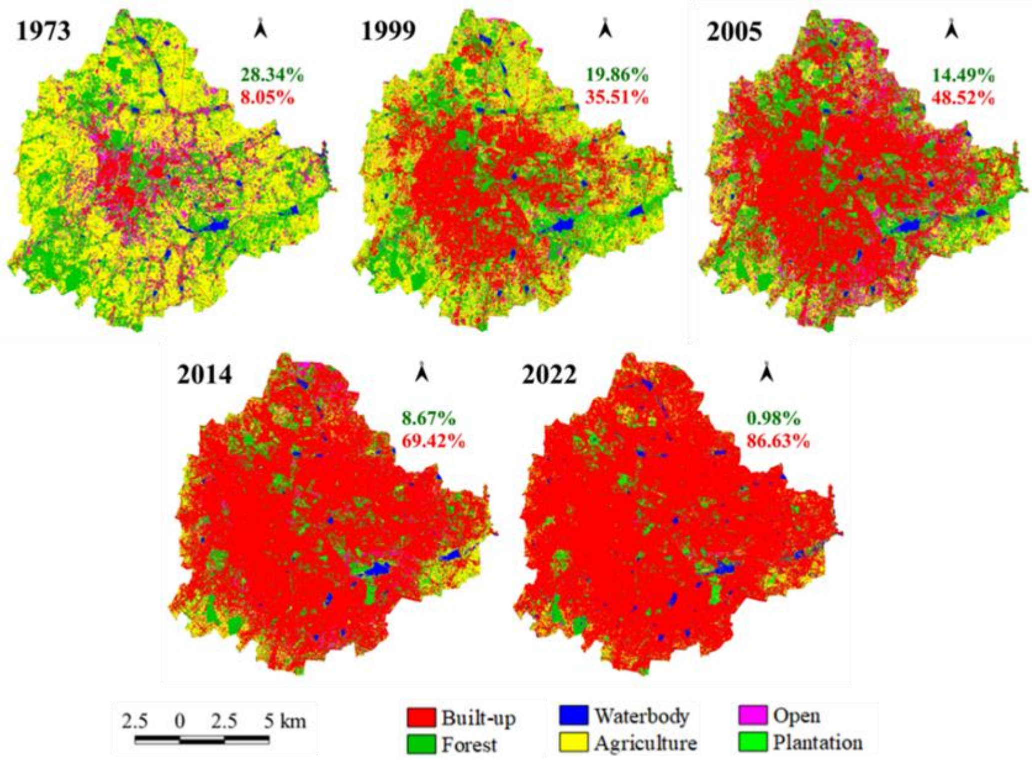


Figure 8 Rapid urbanisation in Bangalore city.

Table 5 Land use changes in Bangalore city (BBMP) from 1973 to 2022.

BBMP		1973	1999	2005	2014	2022
Built-up	sq. km	57.27	252.62	345.14	493.88	616.25
	%	8.05	35.51	48.52	69.42	86.63
Forest	sq. km	201.64	141.26	103.11	61.66	6.96
	%	28.34	19.86	14.49	8.67	0.98
Waterbody	sq. km	13.01	11.04	15.13	13.67	14.88
	%	1.83	1.55	2.13	1.92	2.09

Agriculture	sq. km	367.06	238.41	139.14	47.91	39.54
	%	51.60	33.51	19.56	6.73	5.56
Open	sq. km	71.77	27.08	56.40	19.15	3.58
	%	10.09	3.81	7.93	2.69	0.50
Plantation	sq. km	0.64	40.99	52.48	75.13	30.19
	%	0.09	5.76	7.38	10.56	4.24

3.3 Forest Fragmentation

Conservation of biodiversity is possible by maintaining ecological integrity, which has been assessed through metrics to understand the fragmentation of forests (Figure 9, Table 6). Quantifying forest fragmentation would help formulate appropriate mitigation measures for improving the condition of forest ecosystems, and the analyses showed that the interior forest area had declined from 9.75% (in 1973) to 1.68% (in 2022).

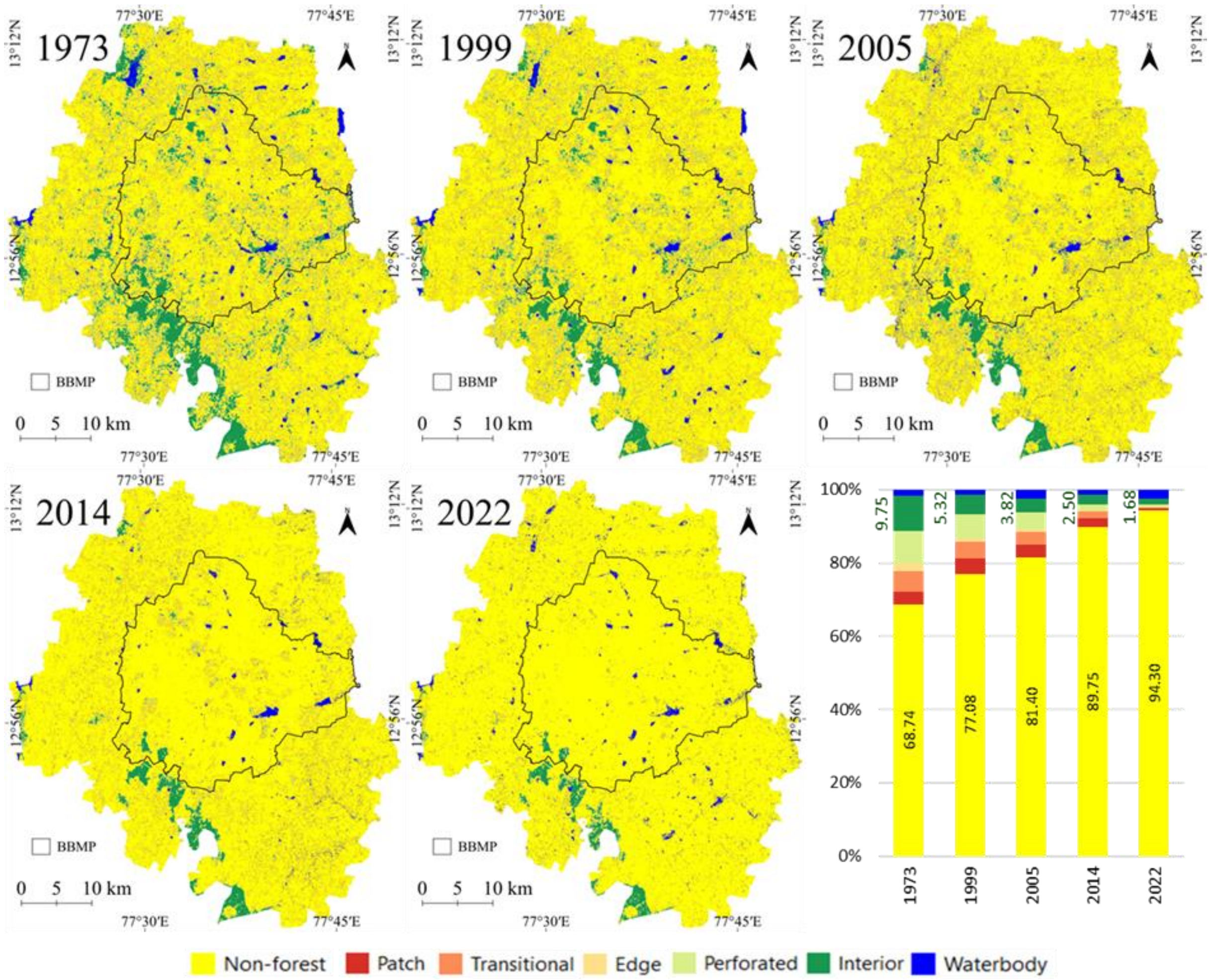


Figure 9 Forest Fragmentation Analysis of Bangalore Urban from 1973 to 2022 (Source: Author).

Table 6 Forest Fragmentation Analysis of Bangalore Urban from 1973 to 2022.

		1973	1999	2005	2014	2022
Non-Forest	sq. km	1510.58	1693.92	1788.81	1912.58	2072.48
	%	68.74	77.08	81.40	87.03	94.30
Patch	sq. km	72.50	93.28	78.43	41.26	13.44
	%	3.30	4.24	3.57	1.88	0.61
Transitional	sq. km	125.32	100.67	77.72	41.89	7.22
	%	5.70	4.58	3.54	1.91	0.33
Edge	sq. km	47.79	20.14	14.05	7.98	1.97
	%	2.17	0.92	0.64	0.36	0.09
Perforated	sq. km	190.81	139.91	101.87	55.29	13.35
	%	8.68	6.37	4.64	2.52	0.61
Interior	sq. km	214.19	116.89	83.87	68.17	36.99
	%	9.75	5.32	3.82	3.10	1.68
Waterbody	sq. km	36.46	32.84	52.90	70.48	52.19
	%	1.66	1.49	2.41	3.21	2.37

3.4 Prediction of Likely Land Uses-Modelling

Prediction of likely land uses would help in framing appropriate land management policies for conserving biodiversity and maintaining ecological balance. Modeling of likely land uses has been done with the help of Markov and Cellular Automata (MCA) to understand future land use transitions based on the current transitions. Likely, land uses (predicted) were compared with the actual land uses. Higher kappa and overall accuracies confirm the robustness of the modeling approach. The computation of user, producer, and overall accuracy (of 91.45%) shows relatively higher accuracies across all land uses. (Table 7, Figure 10). The validation values were K_{no} = 0.9381, $K_{location}$ = 0.9516, $K_{locationStrata}$ = 0.9516, and $K_{standard}$ = 0.9235, and they suggest a good performance of the modeling technique. Subsequently, using current period land-use transitions, predicted land uses of 2030 and 2038 (Figure 10) highlight further degradation of forests by 0.65% in 2038. Similarly, the area under agriculture will likely decrease to 27.03% in 2030 and 22.4% in 2038.

Table 7 Actual land use in 2022 and simulated land use for 2022, 2030, and 2038 in Bangalore Urban district.

	2022 actual		2022 Simulation		2030 Simulation		2038 Simulation	
	sq. km	%	sq. km	%	sq. km	%	sq. km	%
Built-up	1224.27	55.71	1246.92	56.74	1381.19	62.85	1536.08	69.90
Forest	72.97	3.32	121.92	5.55	28.22	1.28	14.32	0.65
Waterbody	52.19	2.38	38.93	1.77	61.25	2.79	52.21	2.38
Agriculture	723.24	32.91	673.81	30.66	593.96	27.03	492.19	22.40
Open	45.93	2.09	46.88	2.13	54.34	2.47	46.91	2.13
Plantation	79.03	3.60	69.19	3.15	78.68	3.58	55.94	2.55

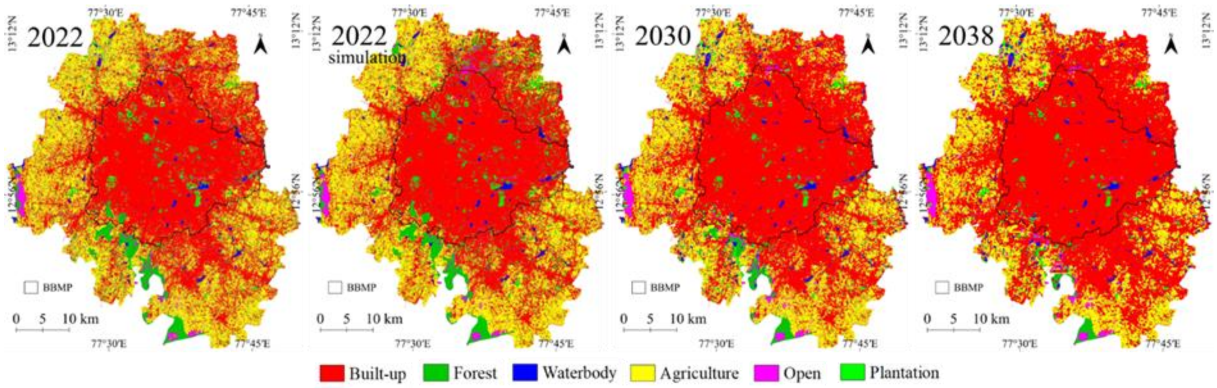


Figure 10 shows actual land uses and simulated land uses for 2022, and a prediction of land uses for 2030 and 2038 in the Bangalore Urban district (Source: Author).

4. Discussion

Spatial analyses using temporal remote sensing data reveal the decrease in vegetation cover in the rapidly urbanizing city landscape (under BBMP jurisdiction) and in its neighborhoods after globalization and liberalization of the market economy in the 1990s. Locations such as Koramangala and Hosur witnessed the growth of IT companies with the announcement of favorable IT policies by the State government. Post 2000, the Electronic City, Whitefield's eastern and southeastern parts witnessed a boom in IT hub and industrial growth in Peenya and along the city's outer ring road, leading to the transition of open spaces (with vegetation and water bodies) to paved urban spaces. Increased commercial activities triggered residential growth across the eastern part of the district. Due to the city's expansion, the surrounding forest area and green spaces have declined in the last five decades, affecting the native biodiversity in the region. Rapid urbanization lacked planned interventions, and increased paved surfaces indiscreetly affected the natural drainage network and groundwater recharge, leading to frequent flooding and severe groundwater scarcity.

Mapping of trees using higher spatial resolution remote sensing data revealed that Bangalore city has a tree population of 14,78,000, which accounts for one tree per seven persons (considering the population of 9.5 million (excluding floating population) contrary to the requirement of seven trees per person [42, 43]. This has contributed to oxygen deficiency in the region. The acute water crisis (due to insufficient recharging of groundwater) and oxygen scarcity (due to the reduction of tree cover) are pushing Bangalore City toward unliveable status [44].

Rapid urbanization in Bangalore has resulted in increased air pollution levels, which have shown PM_{10}, $PM_{2.5}$, and NO_2 more than the national ambient air quality standard because of the rise in vehicular emissions, industrial activities, and construction projects in and around Bangalore city [45]. The mushrooming of IT companies and the subsequent population growth have impacted the basic infrastructure, which became evident from the increased traffic congestion in the city [32, 33]. Unplanned urbanization has strained existing infrastructure systems, including transport networks, groundwater resources, sewage systems, water supply, and waste management [46]. The increase in paved surfaces and the reduction in green spaces have contributed to the urban heat island effect in Bangalore, with increased Land Surface Temperature (LST) from 33.07°C to 41.14°C (in urban areas) of March to May from 1992 to 2017 evident from the analyses of Landsat thermal band data through computation of NDVI (normalized difference vegetation index), emissivity, brightness temperature, etc. [34]. The decline of heat sinks like water bodies and the green cover has negative impacts on the local microclimate, evident from the reduced cooling effect, increase in land surface temperature, and consequent increase in electricity consumption, which has increased vulnerability and exposure to environmental risks and hazards.

Also, urbanization spreading in the surrounding areas of the municipality (Bruhat Bangalore Mahanagara Palike, BBMP) has resulted in a significant loss of agricultural land and the livelihood of farmers with reduced farm output and a decrease in farmers' income [41]. The conversion of natural habitats like wetlands and green spaces into urban spaces has resulted in biodiversity loss and eroded soil quality in and around Bangalore [36, 47]. The accelerated urbanization of the city has exerted considerable pressure on its waste management systems due to inadequate infrastructure for the proper processing of solid waste [48-50]. Consequently, this has led to environmental degradation in the surrounding areas and the city. The key ecological and environmental impacts in the neighborhood of Bangalore city due to rapid and uncontrolled urbanization are loss of vegetation, water bodies, and open spaces, the decline of native biodiversity, contamination of air and water due to pollution, higher GHG emission, water scarcity with the depletion of groundwater due to lack of recharge, urban heat island and alterations in a micro-climate, prevalence of vector-borne diseases with escalating temperature, etc. [44, 47]. The urban heat island effect would enhance the ambient temperature and humidity levels, resulting in heat stress and heat-related illnesses, including behavioral changes [15, 28, 42-44, 51].

Rapid urbanization has changed the composition and diversity of the vegetation near Bangalore city. The native vegetation, such as grasslands, wetlands, and scrublands, has been replaced by exotic species. Urban green spaces provide various benefits for urban residents, such as recreation, aesthetics, cooling, air purification, noise reduction, etc. Degradation of green and blue spaces would lead to impaired ecological functions and services.

Spatial analyses of landscape dynamics reveal that rapid urbanization in Bangalore city has affected the condition of ecosystems, evident from the fragmentation of forests, contamination of water bodies due to sustained inflow of the city sewage, disposal of untreated industrial effluents, and dumping of solid waste in lake beds. The decline of ecosystem conditions has led to the reduction and fragmentation of contiguous native forests, decrease of native vegetation, spread of invasive exotic species, increase in land surface temperature, and consequent increase in vector-borne diseases [44]. The habitat loss and fragmentation reduce the availability and suitability of resources for various flora and fauna species, which affects their survival, reproduction, and dispersal. The loss of native vegetation and the invasion of exotic species alter the interactions and relationships among different species, which affects their adaptation and evolution. The loss of habitat and species diversity also reduces the genetic variability and resilience of the ecosystems. The decline of ecosystem services also increases the vulnerability and exposure of the urban population to environmental risks and hazards.

Insights from the analyses of rapidly urbanizing landscapes (such as Bangalore city) would help evolve strategies for designing sustainable cities with liveable conditions, adequate infrastructure, and basic amenities while maintaining essential green and blue spaces through effective enforcement and implementation of land-use policies.

5. Conclusion

Globalization and subsequent liberalization of Indian markets during the 1990s gave impetus to rapid urbanization in the Bangalore urban district with a spurt in industrial and infrastructural activities. Unplanned developmental activities leading to rapid changes altering land uses in the region had adverse ecological and environmental impacts, evident from the decline of forest cover (by 26%), agricultural lands (by 23%), with a sharp escalation of paved surfaces (urban area 34% increase in five decades). The implication of continuation of this trend, visualized likely land uses in 2038 through the Cellular automata Markov technique, highlights that the city of Bangalore will be choked with paved surfaces (to the extent of more than 98%) and 69.9% of the landscape in the Bangalore Urban district would be paved areas. This highlights the consequence of a dying city (Bangalore) with unplanned irresponsible urbanization, which caused undesirable effects on the neighborhood areas and drove the entire landscape to an unliveable status, with reduced ecosystem services, poor environmental conditions, and increased vulnerabilities that impact people's livelihood.

Planned urbanization would promote efficient land utilization, minimizing sprawl while ensuring all residents' basic amenities and infrastructure. Planned interventions would reduce the alteration of natural systems (forests, water bodies, and agricultural lands), optimize mobility with land uses to reduce greenhouse gas footprint, and promote the conservation of lung spaces (greeneries–parks, etc.) and kidneys (wetlands) of the landscape and ensures reuse and recycle of wastes (solid and liquid). This would sustain ecosystem services (provisioning, regulating, and cultural services) through enhanced recreation services for the urban population, moderate microclimate, groundwater percolation due to adequate permeable and porous spaces, and livelihood of the dependent population.

Therefore, the study highlights the need for planned urbanization and decongestion of the region by shifting large-scale industries, allowing future developments in other parts of Karnataka state to ensure liveable conditions through prudent management strategies. This will ensure sustainable development and the preservation of ecosystem services for intergenerational equity, ultimately leading to a liveable region. Machine learning technique adopted through the Google engine to classify temporal remote sensing data has been tried in other areas [35]. Accuracy assessment indicates consistent results, highlighting the robustness of the supervised non-parametric classifier compared to parametric classifiers in assessing the extent of urbanization and condition of ecosystems (through fragmentation of forests) and geo-visualizing likely land use changes in the neighborhood with the current path of rapid urbanization.

RF classifier has been implemented because it uses numerous decision trees for computation, which can make the process relatively complicated. A single query to Earth Engine is limited to 10MB in size, and the size limit on computed results is 100 MB, which can cause an error, especially while performing multivariate analyses (such as PCA, etc.) restricting dimensions of the input data. However, RF is the robust classifier for multispectral data with adequate training data.

Scope for future research includes geo-visualization of likely land uses considering agents of land use transitions and consideration of planned urbanization, which include provisioning 15% open spaces, conservation of greeneries and water bodies, maintaining at least 33% green cover, enhancing groundwater recharge potential, rainwater harvesting, climate resilient building architecture, etc. for prudent management of natural resources.

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Author Contributions

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