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A GEOSPATIAL STUDY OF THE CHANGES IN LAND USE AND FORECASTING IN COIMBATORE CITY USING QGIS

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Abstract

The most talked-about topic in the world has always been urbanization because of its complexity and the fact that it is a continuously changing global phenomena. Understanding the LU/LC change in the urban landscape is essential to comprehending the current state of the city and the dynamics of the earth's surface change. This study's objectives are to show and explain how LULC trends varied between 2011 and 2021and to forecast future LULC mapfor 2030.The open-source plugin MOLUSCE (Modules for Land Use Change Simulations) version 3.0.13 was utilized to forecast the future plight of urbanisation of Coimbatore city. According to the predicted model by using, the geospatial tools, the land under urban area will substantially rise from 128.29 sq kms in 2021 to 151.47 sq kms in 2030. In contrast, the area under water bodies, vegetation, and agriculture is showing a decline trend. Urban growth dynamics and spatial patterns of urban expansion is a very relevant study to equip, both the policy makers and stake holders.To carve out a sustainable city by all means, with all the necessities, this article can be considered by urban planners and developers, local governments, and non-governmental organizations, public and private enterprises, and certain social well-wishers, in their attempts to create more sustainable urban environments in the city.

Key words: *Urbanisation, LULC, MOLUSCE, and Sustainable*

1. Introduction

The industrial revolution of the 18th and 19th century was a major cause for the current growth and sustenance of towns and cities. The post-industrial revolution saw an upsurge in people moving from under developed rural villages to developed urban areas. This gave rise to the growth of numerous urban centers as well as the expansion of already existing towns and cities. Urban growth and development are hot topics everywhere in the world. Numerous environmental issues have arisen as the urban population has grown. The constantly growing population seeks to have all of its demands met, including socioeconomic and resource management needs. According to "World Population Prospects 2022: Summary of results," (2022) the global population will increase by 8.5 billion, 9.7 billion, and 10.4 billion people by 2030, 2050, and 2100, respectively. The global urban population in 2021 was 56.61%, and by 2050, it is projected to increase by 68% (World urban population, 2021). As the world's population continues to rise, it is crucial for urban designers and planners to anticipate the city's needs in order to develop plans for a sustainable city.There are numerous rule-based and transportation-based forecasting methodologies utilized to look into the global urban LULC changes.They consist of the following, CUF (California Urban Futures), QUEST, UrbanSim, DUEM (Dynamic Urban Evolutionary Model), SLEUTH (Slope, Land-use, Exclusion, Urban extent, Transportation, and Hill shade) is a modified CA model, CAST (City Analysis Simulation Tool), SIMLUCIA, DINAMICA, UES (Urban Growth Scenario), Fuzzy Cellular Automata Urban Development Model (FCAUGM), IDRISI'S CA MARCOV, Cellular Automata model (CA), CLUE (Conversion of land use and its effects), and MOLUSCE.Both the public and private sectors make extensive use of opensource software. Particularly the QGIS is being developed more actively with numerous specialized plugins (quickhelp.pdf). The MOLUSCE (Modules for Land Use Change Simulations) model was created by Asia Air Survey (http://www.asiaairsurvey.com) and NextGIS (http://nextgis.com) in the twenty-first century and is a well-known cellular automata and Artificial Neural Network (ANN) based urban growth simulation model. For the purpose of simulating and validating the LU/LC modifications maps, this plugin includes a number of features.It is crucial in every way to predict how the city's land usage will develop in the future. As a result, the open-source QGIS plugin MOLUSCE (Modules for Land Use Change Simulations) version 3.0.13 was loaded and utilized to forecast the current study of Coimbatore city. This model was based on simulation using cellular automata and ANNs. Additionally, it has a better ability to compute urban land use change models. MOLUSCE combines well-known techniques that can be applied to forestry applications, urban studies, and simulations of land use/cover change. Incorporating ANN, LR, WoE, MCE, and kappa statistics for validation, the algorithm (MOLUSCE Introduction) also uses WoE.BoasherWillayat (Al-Rubkhi, 2017),Malang City (Nugroho, 2018), Kaysone PhomvihanDistirct (Mienmany, 2018), Greater Bay and Bangladeshi Dhaka Metropolitan (Abbas et al., &Kafy et al., 2021), Thiruvananthapuram Urban Agglomeration (Chettry&Surawar, 2021), Bhavani Basin in Tamil Nadu (Kamaraj &Rangaraja, 2022), and Mand catchment of the Mahanadi Basin in Chhattisgarh (Baghel et al., 2024) are all places where MOLUSCE tool has been successfully applied.MOLUSCE is a good tool to Examine the variations in urban land usage throughout two time periods and to Predict future changes in land use and cover.

1.1 Objectives

The specific objectives are

- To map the study area by evaluating land use/land cover changes using geospatial tools.
- To investigate the trend of urban growth in terms of land use.
- To predict the future trends of the spatial growth of Coimbatore city using the MOLUSCE (Modules for land use change simulations) plugin model in QGIS.

2. Study Area

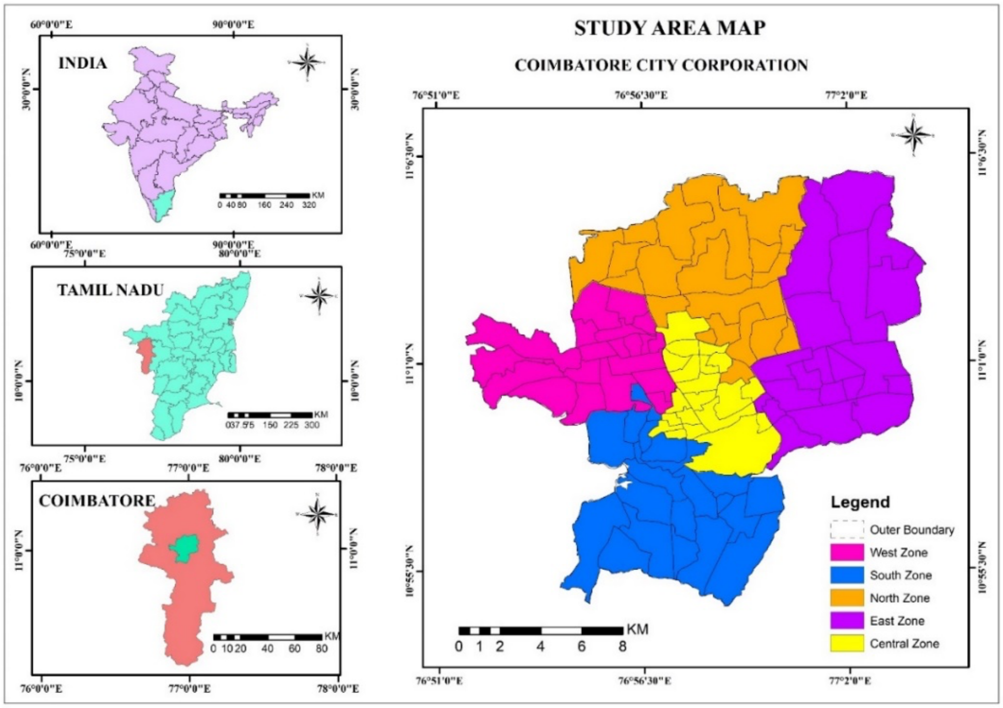

Fig. 1: Location Map of the Study Area

Coimbatore City is situated between 10°54'36" and 11°06'17" N latitude and 76°52'13" and 77°97'25" E longitude in the extreme west of Tamil Nadu, close to Kerala State with an area of 257 sq. km (Fig. 1). On average, the city is 432 meters above sea level. The Vellingiri hills in the west are the source of the river Noyal, which runs through the heart of the city. The metropolitan area of Coimbatore has 16 lakh residents, according to the 2011 census. Major Indian cities are easily accessible by road and train from the city. At Peelamedu, 11km outside the city, Coimbatore's international airport offers air service to all significant Indian cities as well as to overseas locations (District Energy in Cities Initiative in India, 2017).

3. Data and Methodology

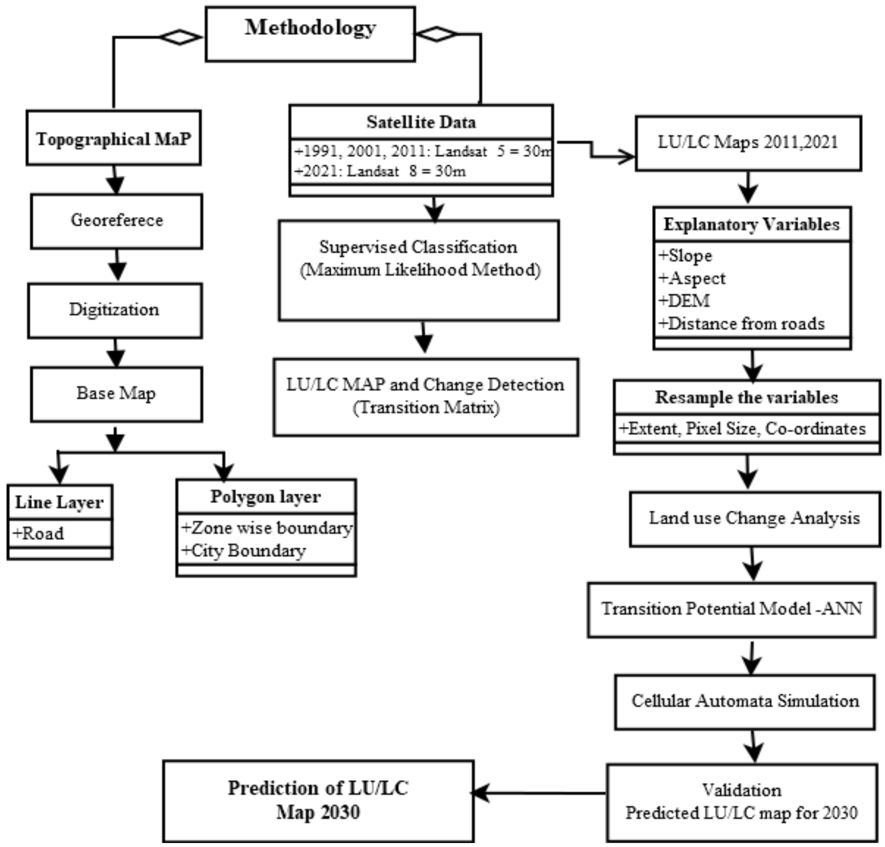

Fig.2: Flowchart of the Methodology

The study relies on secondary data. Basic information such as drainage, transportation, and water bodies were extracted using SOI toposheet of 58A/16, 58B/13, 58E/4, and 58F/1 on 1: 50,000 scale. In order to create DEM, slope, aspect map of the study area, SRTM DEM data was utilized.Besides this DEM, slope, aspect, distance to road maps were prepared with the help of GIS software from Collateral data.Earth explorer.usgs.gov.in was used to collect remote sensing data such as Landsat TM (2011), and Landsat 8 (2021) (OLI/TIRS). Using GIS and remote sensing techniques, a temporal study of land use and land cover changes was conducted based on supervised classification.The MOLUSCE plugin in QGIS was installed and run to predict Coimbatore's urban growth for the year 2030 (Fig. 2).

4. Simulation Functions of MOLUSCE plugin

4. 1. Input variables:

The land use/cover change map for the starting year (2011) and the ending year(2021) is included in this step, along with its spatial variables like DEM, Slope, Aspect, and Distance to Roads (Fig.3). The properties of the explanatory maps as well as the land use/cover change maps (Fig.5) are extracted and converted into the same datasets (i.e., date source like raster information, extent, and spatial reference).These maps were projected using UTM 44N, which consists of 757,714 columns and rows, and a resolution pixel size of 50 meters. After that, the new window appeared as the geometry is matched as a result of this plugin checking all the input raster data (Fig. 4).

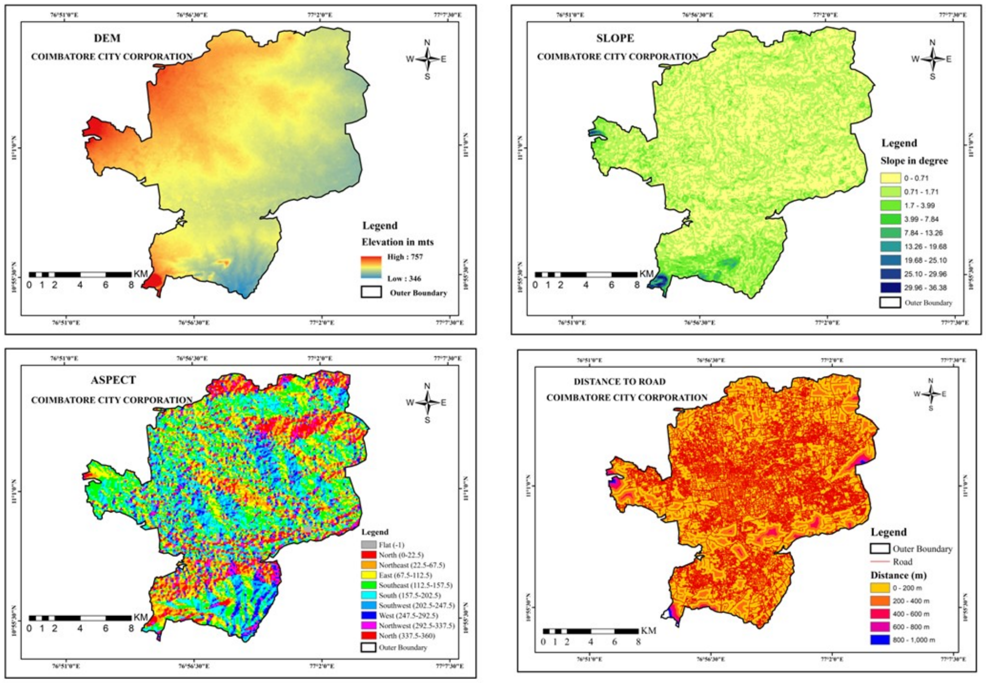

Fig.3: Explanatory Variables: Digital Elevation Model, Slope, Aspect and Distance to Road

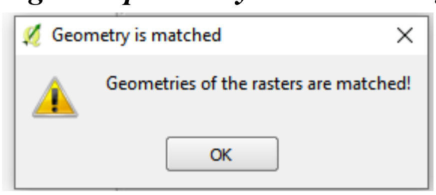

Fig.4: Checking of the Input variables

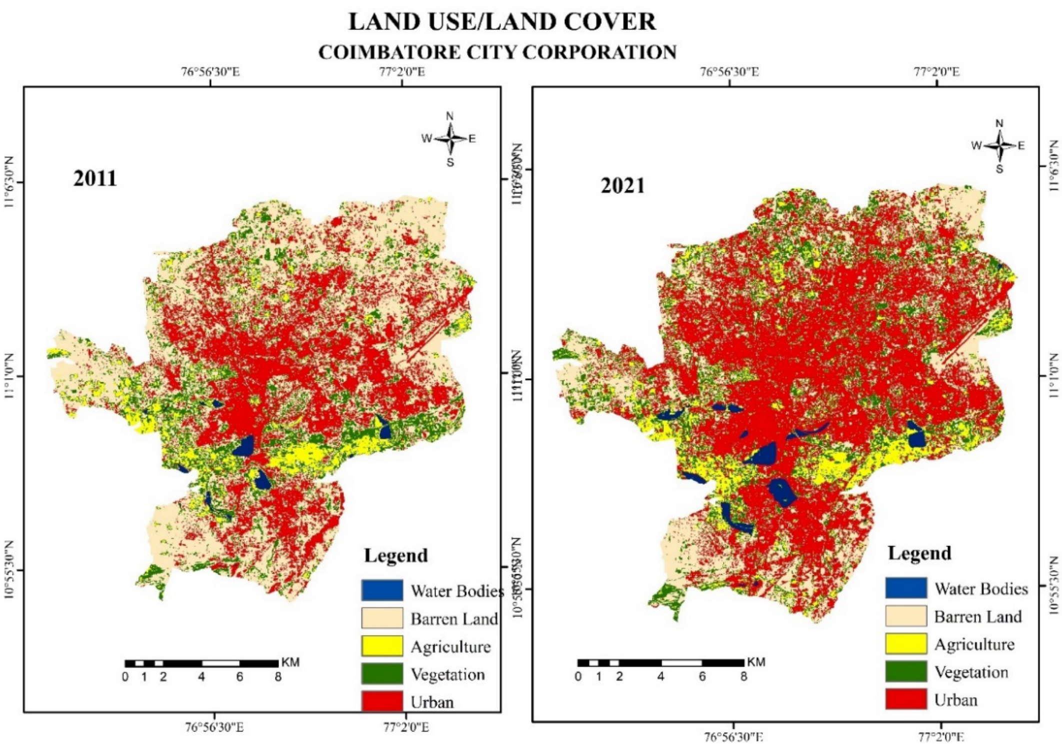

Fig 5: LU/LC Map (2011 & 2021)

4. 2. Pearson's correlation:

The table 1 shows the Pearson correlation coefficients for four geographical variables: aspect, slope, DEM, and distance to highways. Pearson's correlation coefficient may be used to establish the linear relationship between the direction and strength of two variables. It lies in the range of -1 to 1, where:

Table 1: Pearson's Correlation between variables

	Distance to Roads	**DEM**	**Slope**	**Aspect**
Distance to Roads	--	0.111919891234	0.304358360432	-0.00476390873453
DEM		--	0.394378633288	-0.0462861399696
Slope			--	0.60828831311444
Aspect				--

- A correlation value of one indicates a full positive linear link. In proportion to the growth in the first variable, the other variable also grows.A correlation value of -1 indicates a fully negative linear link. The decline in the other measure is directly correlated with the increase in the first.If there is no linear relationship between the two variables, the correlation coefficient is 0.

The four variables in the table have correlation coefficients ranging from -0.046 to 0.608. A summary of the correlations in the table is provided below:

- The highest positive correlation is found between Aspect and Slope (0.6082). This indicates that these two variables have a reasonably strong linear connection. The aspect tends to grow along with the slope.There is a somewhat positive connection (0.3943) between DEM and Slope. In comparison to slope and aspect, this indicates a less linear connection between these two factors. Though it is not as powerful, there is still a good tendency. There is little to no linear relationship between any of the other correlations' values, which are all near zero.

4. 3. Area Change Analysis:

Class statistics

sq. km.

	Class color	2011	2021	Δ	2011 %	2021 %	Δ %
1		2.66 sq. km.	5.60 sq. km.	2.94 sq. km.	0.975262126441	2.05280140417	1.07753927773
2		130.26 sq. km.	75.75 sq. km.	-54.51 sq. km.	47.7522121558	27.7682465737	-19.9839655821
3		16.40 sq. km.	20.84 sq. km.	4.44 sq. km.	6.01158701146	7.63911342206	1.6275264106
4		39.29 sq. km.	42.31 sq. km.	3.02 sq. km.	14.4026024586	15.508845324	1.10624286534
5		84.18 sq. km.	128.29 sq. km.	44.12 sq. km.	30.8583362477	47.0309932761	16.1726570284

Transition matrix

	1	2	3	4	5
1	0.954330	0.003721	0.014208	0.013194	0.014547
2	0.003489	0.456300	0.024348	0.159981	0.355882
3	0.065199	0.054443	0.566160	0.255968	0.058230
4	0.033330	0.196202	0.203784	0.390388	0.176295
5	0.002705	0.091456	0.004020	0.022527	0.879291

Figure 6: LU/LC Area changes and Transition Matrix

The LU/LC changes between the time period (2011) to (2021) were calculated using this plugin. The changes in the LU/LC area are shown in square kilometers, along with the percentage of the area change, calculated and a transition matrix for the two specified years provided in the given Fig.6.

4. 4. Transition Potential Modelling:

Artificial Neural Network (ANN), Logistic Regression (LR), Weights of Evidence (WoE), and Multi Criteria Evaluation (MCE) algorithms were all calculated using this plugin. In this study, the land use/cover change transition model was predicted using the Artificial Neural Network (ANN) algorithm (Figure 4). While testing the Artificial Neural Network (Multi-layer Perceptron) technique, the following parameters were discovered: Neighborhood - 1px, Learning rate - 0.100, Maximum iterations - 1000 nos., Hidden layer - 10 nos., and Momentum value - 0.050.

A neural network's learning curve is graphed in the figure 7. The graph's x-axis is labelled "Iterations," while the y-axis is labelled "Error." The graph consists of two lines: a green line and a red line. The training error is shown by the red line, while the validation error is shown by the green line.

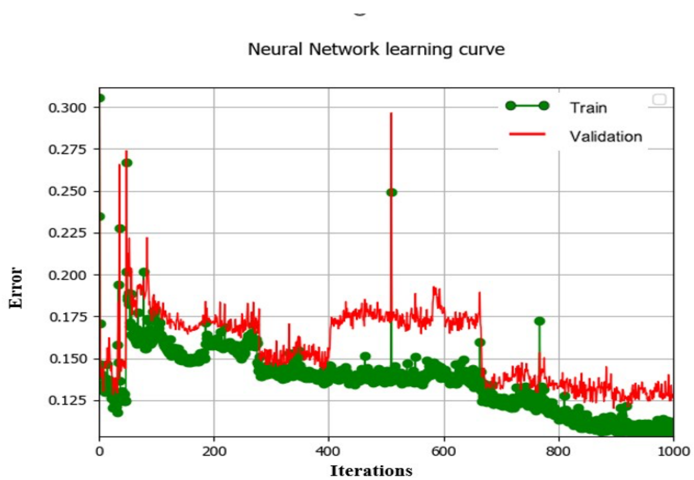

Fig.7: Neural Network Learning

4.5.Cellular Automata Simulation:

The LU/LC map was predicted using cellular automata simulation based on the Monto Carlo algorithm. This method was used to produce a future LU/LC change map for 2030 using the change in LU/LC between 2011 and 2021.

4.6. Validation:

The simulated land use and land cover map for 2030 was used to calculate validation. It calculated the kappa overall accuracy, kappa histogram, and kappa location for the simulated land cover map. Overall accuracy was 0.77673. This is shown in figure 8.

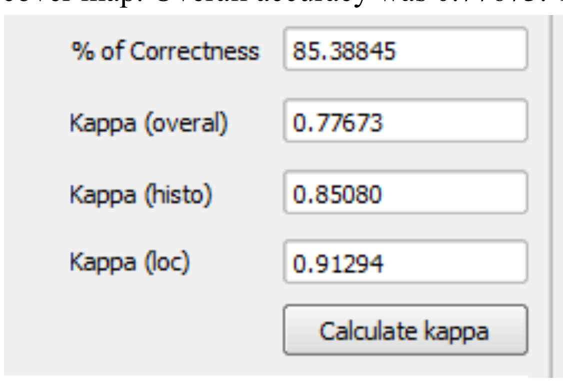

Fig.8: Kappa Validation

4.6.Messages:

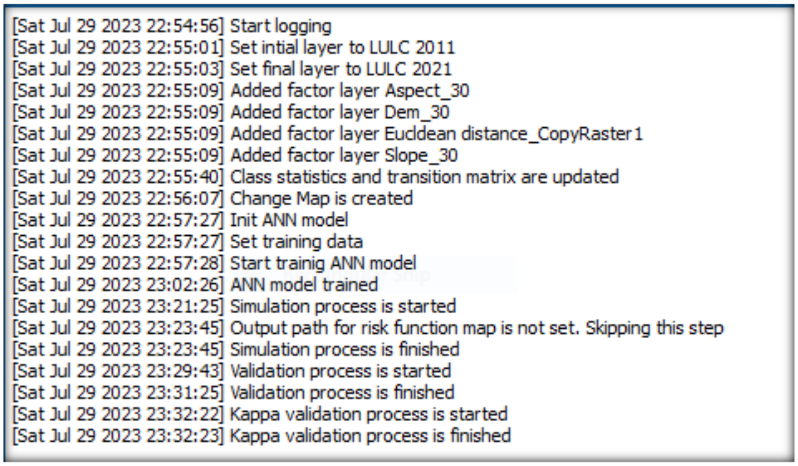

Fig. 9: Processes of the MOLUSCE model's functions

It provided the beginning and ending processes for each of the MOLUSCE model's functions. The beginning and end of each of the seven functions are depicted in the following image figure9.

5. Result and Discussion

5.1.Land use Land Cover Change Analysis between 2011- 2021

Table 2: Area-wise LU/LC changes between 2011 and 2021

Source: Compiled by Author

Feature	**Area in sq km**		**Change of area**	**Changes in LU/LC (%)**		**Changes in LU/LC (%)**
	2011	2021	2011-2021	2011	2021	2011-2021
Water Bodies	2.66	5.60	2.94	0.97	2.05	1.08
Urban	84.18	128.29	44.11	30.85	47.03	16.18
Barren Land	130.26	75.75	-54.51	47.75	27.76	-19.99
Agriculture	16.40	20.84	4.44	6.01	7.63	1.62
Vegetation	39.89	42.31	2.42	14.4	15.5	1.10

The land use analysis of the study area was conducted between 2011 and 2021, as shown clearly in table 2, Figure 5 &10. Due to the significant changes in lu/lc between 2011 and 2021, it is evident that both positive and negative changes have occurred in urban areas (44.11 sq km) and barren land (-54.51 sq km), among other features. The area covered by water bodies grew from 2.66 square kilometers to 5.60 square kilometers; this could be due to the efforts of some NGOs, such as Siruthuli. Between 2011 and 2021, the area covered by urbanization grew from 84.18 to 128.29 square kilometers. Between 130.26 sq km (47.75%) and 75.75 sq km (27.76%), barren land exhibits a significant declining trend. It makes it quite evident that there has been urban encroachment. Additionally, there is a slight rise in the area under vegetation (39.89 sq km to 42.31 sq km) and agriculture (16.40 sq km to 20.84 sq km).

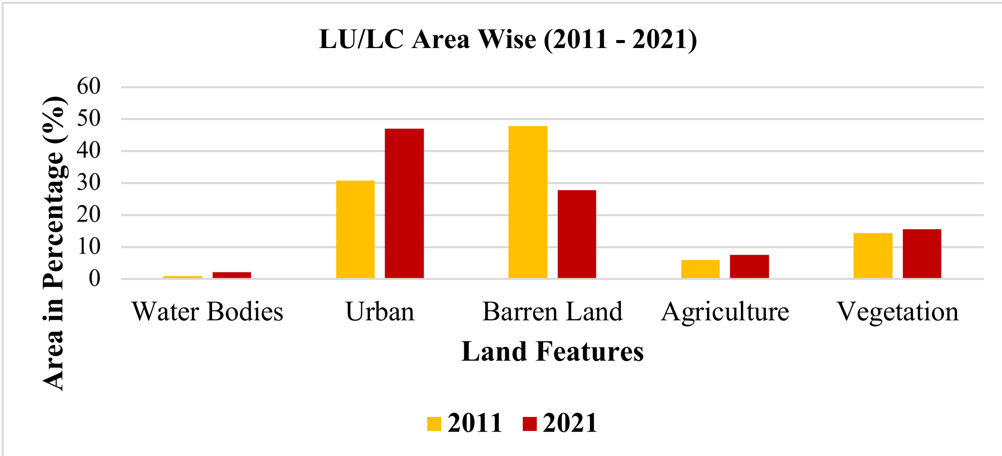

Fig.10: LU/LC Area in Percentage from 2011 to 2021

5.2. Cellular Automata Simulation:

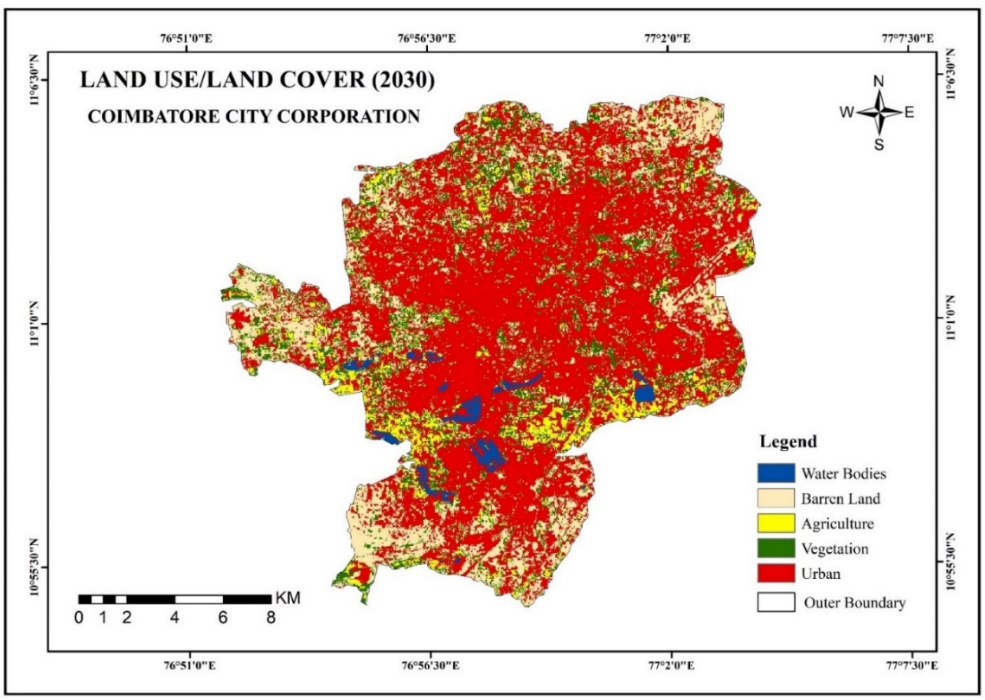

Fig.11: LU/LC Predicted Map (2030)

The change in LU/LC between 2011 and 2021 was utilized to create a future LU/LC change map for 2030 using the Cellular Automata Simulation approach. It is evident from fig.11 & 12, and table 3 that a significant portion of the city is occupied by urban land use. Between 2021 and 2030, the area covered by urbanization grew from 128.29 sq km (47.02%) to 151.47 sq km

(55.52%). This suggests that Coimbatore City's urban area is rapidly expanding and that demand for land is rising.

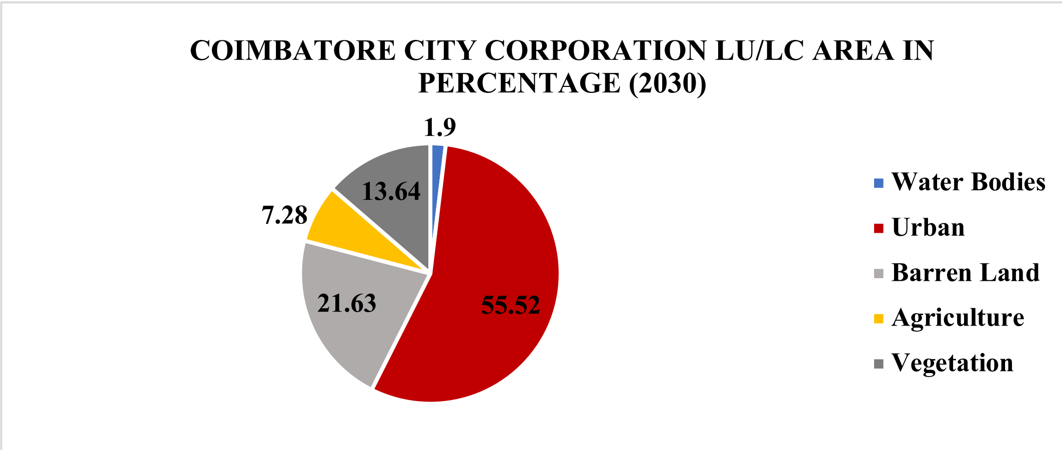

Fig. 12: LU/LC Area in Percentage

Table 3: Coimbatore City Corporation- LU/LC pattern 2021, 2030

Feature	Area in sq. km		Changes in Area (sq. km)	Percentage of total area		Changes in area (%)
	2021	2030	2021-2030	2021	2030	2021-2030
Water Bodies	5.60	5.21	-0.39	2.05	1.90	-0.14
Urban	128.29	151.47	23.18	47.02	55.52	8.49
Barren Land	75.75	59.01	-16.74	27.76	21.63	-6.13
Agriculture	20.84	19.90	-4.94	7.63	7.28	-0.35
Vegetation	42.31	37.23	-5.08	15.51	13.64	-1.86

Source: Compiled by Author

The next highest percentage of land use anticipated in 2030 is barren land, which is estimated to be around 21.63 percent. Land under vegetation will be decreasing from 42.31 to 37.23 square kilometers, and land used for agriculture and water bodies will be decreased from 20.84 to 19.90 sq km and from 5.60 sq km (2.05%) to 5.21sq km(1.90%), respectively. The only land use with positive changes is the urban area; the remaining land uses will be experiencing negative changes. This projected map's overall accuracy was 0.77673.

Table 4: Coimbatore City Corporation- Change Matrix between 2021- 2030

LU/LC Change matrix 2021-2030 Area (in sq. km)					
Feature	**Water Bodies**	**Urban**	**Barren Land**	**Agriculture**	**Vegetation**
Water Bodies	0.93	0.24	0.25	0.16	NA
Urban	NA	0.96	0.01	0.02	NA
Barren Land	NA	0.29	0.60	NA	NA
Agriculture	NA	0.04	0.04	0.42	NA
Vegetation	NA	0.07	0.07	0.15	0.52

Source: Compiled by Author

Table 4obviously shows that the major changes in the urban fabric occurred in the change matrix between 2021 and 2030. 0.24 sq km of water bodies, 0.29 sq km of barren land, 0.04 sq km of agricultural land, and 0.07 sq km of vegetation is predicted to be converted into urban land.

6. Conclusion:

The predicted LU/LC analysis revealed that the area has been massively grown, notably the area under urbanization, which has increased from 128.29 sq kms in 2021 to 151.47 sq kms in 2030, while the area under barren terrain, water bodies, and vegetation and agriculture has declined negatively. The proposed LU/LC can play an important part in the creation of a sustainable city. It can be used as a base data while proposing infrastructure facilities like new roads, settlement patterns, metros, overbridges, and other buildings by urban planners, decision makers and infrastructure planners to achieve a wholistic and sustainable Coimbatore city. The predicting the scenario of Coimbatore City's Urbanization trend in 2030, revealed that the city is expanding towards the urban fringe in all direction except for the barriers of hills (Western Ghats). Therefore, it is essential and very important to avoid overcrowding of population and its associated difficulties, and planning ahead is vital. Considering this expected increase proper urban planning needs to be done to address the issues of traffic congestions, accidents, rising land values, rising costs of living, garbage disposal, water shortage and so on. These findings will assist researchers, corporation officers, government officials, non-governmental organizations, and other city planning authorities in providing sufficient quality of life to the people through outstanding public services and for designing urban planning of the city. The outputs of the current study draw attention to the necessity of ecological sensitivity in urban planning and development processes in order to guarantee the city's long-term survival.

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