Cloud-based Geospatial Analysis to Assess LULC Changes and Prediction of Future Scenario Using a Coupled CA-ANN Model: Case Examples from Sri Lanka

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Abstract: *The classification of land use / land cover (LU/LC) for certain area plays a major role in planning, management and monitoring programs as well as it helps to study the changes which are happening in the environment and ecosystem. This study aims to evaluate LU/LC changes in Tellippalai DS Area in Sri Lanka. Land use/land cover change evaluation and prediction using spatio-temporal data are crucial for environmental monitoring and better planning and management of land use. The main objective of this study is to evaluate land use/land cover changes for the time period of 2004–2024 and predict future changes using the CA-ANN model in the Tellippalai DS Area in Sri Lanka. Landsat-5 TM for 2004, Landsat-7 ETM+ for 2014, and Landsat-8 (OLI) for 2024 were downloaded from Google Earth Engine. A random forest machine learning algorithm was employed for LULC classification. The LULC classification result was evaluated using an accuracy assessment technique to assure the correctness of the classification method employing the kappa coefficient. Kappa coefficient values of the classification indicate that there was strong agreement between the classified and reference data. Using the MOLUSCE plugin of QGIS and the CA-ANN model, future LULC changes were predicted. Artificial neural network (ANN) and cellular automata (CA) machine learning methods were made available for LULC change modelling and prediction via the QGIS MOLUSCE plugin. Transition potential modelling was computed, and future LULC changes were predicted using the CA-ANN model. An overall accuracy of 91% and an overall kappa value of 0.89 were obtained by comparing the actual data of 2024 with the simulated LULC data from the same year. The study findings revealed that between 2004 and 2014, agricultural land (4.44%) and Bare land (-0.93%) showed significant decreased, and forest (-13.76%) and built up (10.21%) increased. From 2014 to 2024, the built-up area (13.76%) showed a significant increase, forest (-14.5%) decreased and agricultural land (7.61%) showed a significant increased. From 2024 to 2034, the projected LULC simulation result showed that agricultural land (6.6%) and built-up area (4.84%) increased, and forest (-6.98%) and bare land (-4.44%) showed significant decreases. According to the study's findings, the main drivers of LULC changes are the expansion of built-up areas and agricultural land, which calls for a thorough investigation using additional data and models to give planners and policymakers clear information on LULC changes and their environmental effects.*

Keywords: Artificial neural network, cellular automata, Cloud based geospatial analysis, Google Earth Engine, LULC changes, LULC prediction, MOLUSCE plugin

1. Introduction

Land use and land cover change detection are critical processes of environmental monitoring and management. It analyses changes in the characteristics of the Earth's surface over time. It focuses on changes in land use types and land cover classes. Land use is described as human activities and practices on this land, for example, residential, commercial, agricultural and other different activities (Mather,A.S.,1992). Land covers refer to the physical and biological covering on this earth's surface, including water bodies, bare soils, man-made structures, and normal vegetation (Herold, M., and Goldstein, N. C. 2009). The main goal of LULC change detection is to identify and quantify the spatial and temporal dynamics of naturally driven land change processes and human interventions. Due to the huge population growth and rapid expansion of the buildup area, LULC change becomes rapid. In that scenario, a LULC change monitor is now in urgent need because of the need to identify natural hazards-prone areas, whether earthquakes, floods, or any other phenomena (Singh et al., 2018). Land use and land cover (LULC) analysis improves informed decision-making regarding urban development, infrastructure planning, and resource management (Pontius Jr. & Millones, 2011). The detection of LULC changes is an important tool for assessing the many impacts of human activities, climate change, and natural disasters on ecosystems (Foody et al., 2001). There are many techniques used in LULC change detection works. Remote sensing enabled the rapid, cost-effective, and highly accurate analysis of land cover changes (Kanchwala, 1985) in association with the Geographical Information System (GIS) that provided a suitable platform for analysing data, updating, and retrieving. Remote sensing technology, such as including satellite and aerial photography platforms, is widely utilized to analyse spatial and temporal changes in the LULC, and GIS-based analysis helps integrate multitemporal spatial data for mapping and quantifying the changes in LULC (Lu et al., 2004). In recent times, different advanced techniques have been applied in quantifying LULC change, such as advanced machine learning algorithms like Random Forest, support vector machines, Boost, and others that are applied in different areas. Also, deep learning techniques such as CNN and ANN are applied for monitoring land use and land cover changes ((Friedl & Brodley, 1997). The Tellippalai DS area is one of the Divisional Secretariat areas in the northern part of Sri Lanka. The area has experienced rapid development for nearly 20 years, due to new settlements, thereby causing significant changes in land use and land cover (LULC) patterns in the region but there is a lack of comprehensive understanding of the extent, nature, and causes of these LULC changes. Therefore, the problem of this study is to investigate the LULC changes in the Tellippalai DS area through remote sensing-based temporal analysis by investigating the underlying causes of change, identifying and quantifying the spatial and temporal changes in land use and land cover classes over a specific period to show, it is very important to know the nature and extent of these changes. And to determine the direction of its future expansion. To achieve this goal, remote sensing data from Landsat 5, 8, Google Earth Pro Satellite Images, and Google Earth Engine are applied to detect LULC changes in the Tellippalai DS area. The main objective of the present study is to detect changes in land use and land cover in the Tellippalai DS area, in Sri Lanka. To attain this objective, identify and classify different Land use & Land cover types using Landsat imagery of 2004, 2014, and 2024 and future predict the LULC map for the year 2034.

1.1 Statement of the problem:

The Tellippalai DS area is one of the Divisional Secretariat areas in the northern part of Sri Lanka. The area has experienced rapid development for nearly 20 years, due to new settlements, thereby causing significant changes in LULC patterns in the region but there is a lack of different understanding of the extent, nature and causes of these LULC changes. Therefore, the problem of this study is to investigate the LULC changes in the Teleppalai DS area through remote sensing-based temporal analysis by investigating the underlying causes of change, identifying and quantifying the spatial and temporal changes in land use and land cover classes over a specific period to show, it is very important to know the nature and extent of these changes. And to determine the direction of its future expansion. To achieve this goal, remote sensing data from Landsat 5, 8 and Google Earth Pro Satellite Images will be used to detect LULC changes in the Tellippalai DS area.

This is one of the problems in the field of remote sensing and Geographic Information System (GIS) is related to the analysis and characterization of changes in land use and vegetation cover (LULC), the described methodology has applied to a case study in the Tellippalai DS area.

This is done to determine changes and the rate of changes occurring to land cover and land use in Tellippalai and surrounding areas. This will help to assess rate of growth of the Tellippalai DS area and assist in the urban growth planning, development and redevelopment of the DS area.

1.2 Objectives:

In this work the objective of the present study is to detect change in LULC in Tellippalai DS area, in Sri Lanka. To attain this objective, following sub-objectives are framed:

- To identify and classify different Land use and Land Cover (LULC) types using Landsat imagery of 2004, 2014, 2024
- Evaluate Land use and Land Cover (LULC) change of Tellippalai DS area in 2004-2024
- Predict LULC map For Year 2034.

2. Literature Review

Land Use and Land Cover change (LULC) is a complex phenomenon caused by several natural and anthropogenic reasons, and it impacts the pillars of the environment, development, and ecological sustainability. Remote sensing technology is widely utilized to analyse land use and land cover change by obtaining up-to-date and spatially precise data regarding the changes on the planet's surface. This literature review reviews the main principles, methodologies, and results of change detection, post-classification, and change assessment procedures in the context of LULCC analysis. (Singh, 1989)

According to Singh (1989), change detection is the process of defining and quantifying variations in LULC patterns over time. It is an active concept in that change detection uses multitemporal and multispectral Satellite images to track how the landscape has changed (Lu et al., 2004). The conceptual framework integrates a spectrum of varying methods and techniques used to analyse changes over varying spatial and temporal dimensions. (Bruzzone & Prieto, 2000)

3. Materials and Methodology:

3.1. Study Area:

Tellippalai DS area (Valikamam North) is a regional division of Jaffna district in Sri Lanka, covering an area of approximately 6059.9 ha (60.59sq km) and characterized by a unique mix of natural landscapes, farms and human settlements That Land this county Use Land Cover (LULC) in the northern part of the country. An illustrative example, reflecting historical and contemporary socio-economic activities Tellippalai DS area ranges from densely populated communities to scattered rural houses reflecting the rich social and cultural fabric of the community Tellippalai DS area is naturally abundant resources and cultural traditions but water scarcity, land conflicts, environmental degradation, socio-economic inequality, etc. There are many risks and vulnerabilities. This area needs land for consumption sustainable use planning, utilization of natural resources, etc. As variables like population expansion, infrastructure development, and climate change amplify all factors, the Tellippalai DS area is a unique place a dynamic, vibrant environment that encourages sustainable and inclusive development, protects the integrity of life and makes it a natural architecture. Besides these features, the Tellippalai DS area is unique in the use of LULC studies to understand LULC changes and future development.

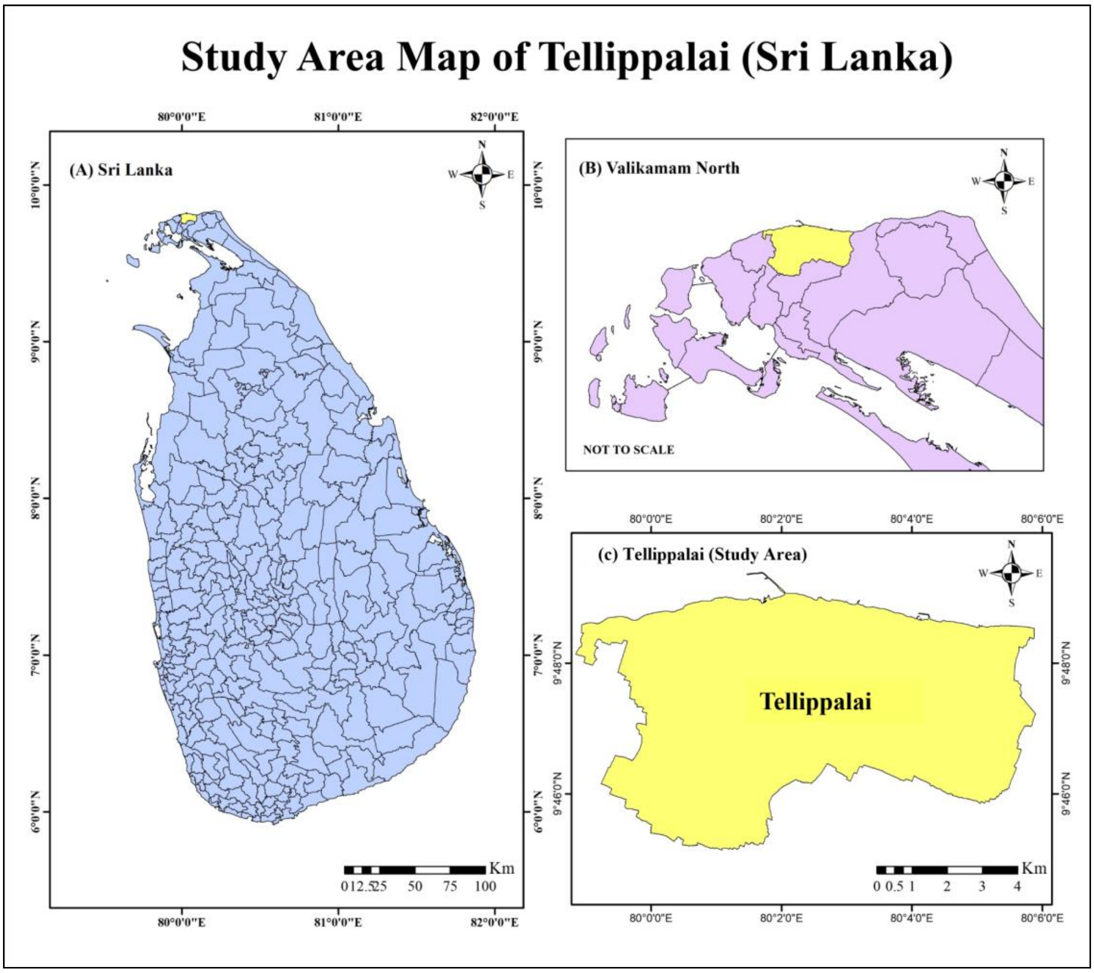

Figure 1: (A) Location map of Tellippalai DS in Sri Lanka, **(B)** Location map of Tellippalai DS in North of States in Sri Lanka, **(C)** Study area map of Tellippalai DS.

3.2. Dataset used and Data Pre-processing:

LULC Classification Data. Landsat 5 from 2004, and Landsat 8 Operational Land Imager (OLI) images, 2014, and 2024, with a resolution of 30 m, were utilized in this study to evaluate changes in LULC in the study region during a 20-year period from 2004 to 2024. Three cloud-free Landsat satellite scenes were downloaded freely from the United States Geological Survey (USGS) website (http://earthexplorer.usgs.gov/).The detailed characteristics of the Landsat images used in this study are presented in Table 1. In this project, we have applied different Remote sensing and GIS software like ArcMap 10.8.2, QGIS 3.28, Google Earth Pro, EARDAS IMAGINE 2014, and Google Earth Engine. The first step involves image pre-processing to correct errors in Landsat images. In this step, merge bands to one image (composite bands-ArcGIS) and clip the image to the study area, and radiometric corrections to enhance the images (haze reduction, noise reduction, etc.) are done. To enhance the identification of vegetation and various defined categories, the bands of clipped images from various periods were organised to create false colour combinations (FCC). The utilisation of ArcGIS 10.8.2 was carried out for remote sensing image processing to facilitate georeferencing and subset of the image based on the Area of Interest (AOI).

3.2.1 Data:

Landsat: the Landsat data downloading from Google Earth Engine (GEE) with 30m resolution from 2004 to 2024.

3.2.2 Software use:

Google Earth Engine (GEE), ArcGIS Pro, ArcMap, QGIS, EARDAS IMAGINE 2014.

- **Google Earth Engine:** This software is a advanced deep learning based which is developed by Google. The software using the Machine Learning language of JavaScript. Some key aspects of GEE are (a) Data Achieve (Landsat, Sentinel-2, MODIS), (b) Cloud-Based Storage, (c) Code Editor, (d) Analytical Capability, (e) Visualization, (f) Collaboration.

  The software Google Earth Engine is a very influential platform to active the conduction geospatial analysis and accumulating for wide range application in fields such as environment, agriculture, forestry, urban planning etc.
- **ArcMap:** The software ArcMap is a component of Esri's ArcGIS Desktop. The software widely using for the Geographic Information System (GIS) mapping and analysis. Through this software the composition provides creating, editing, organizing

this type of environment. By using of this software, the used can use the multiple geospatial layers like shapefile, raster datasets, feature classes. User can export the spatial data to various formats (Shapefile, Geodatabase) the standard format like GeoTIFF, shp, KML. Also, user can access the multiple keys like geoprocessing, map layout and printing etc.

- **QGIS:** QGIS full form of this software name Quantum GIS**.** This is an open-source software for using the Geographic Information System (GIS) analysis. This software is using for the edit, analysing, visualize the spatial datasets. This Software provide some geospatial tool including integration with plugins for analysing the open various datasets.
- **EARDAS IMAGINE 2014:** The software developed by Hexagon Geospatial. The software use for processing, analysing, interpreting the map. The various tools of this software like radiometric correction, geometric correction, atmospheric correction, noise reduction etc. for enhanced the image quality. User can perform the various analysis like change detection, classification, image enhancement by using this software. This software performs for multiple platforms like environment, urban, agriculture analysis including land cover mapping also.
- **Google Earth Pro:** Google Earth Pro is an advanced mapping software which is a desktop-based software. That software has the 3D feature explorer tool also the time scale with the high-resolution image visibility function. In this upgraded version of Google Earth software made with an extra import and export feature.
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Table 1. Description of satellite imageries used in LULC change assessment

Year	Time	Satellite Images	Spatial Resolution	Spectral Resolution
2004	2004/06/25	Landsat 5	30 m	Band 1 to 7 (0.45-2.35)
2014	2014/04/02	Landsat 8	30 m	Band 1 to 11 (0.43-12.51)
2024	2024/01/16	Landsat 8	30 m	Band 1 to 11 (0.43-12.51)

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3.3. LULC Classification and Accuracy Assessment: After Downloading the data and pre-processing the data we classified LULC. In this study, we have taken a total of 5 classes: Agricultural Land, Bare land, Built-up area, Forest, and Water. Here we have applied the Maximum likelihood algorithm used to classify the images. The classification of images was executed to allocate diverse spectral signatures from the Landsat datasets to different Land Use Land Cover (LULC) categories (Congalton & Green, 2009). This process relied on the reflectance properties of the distinct LULC types and was cross-verified using high-resolution images from Google Earth Pro. In this project the kappa-statistic of the confusion matrix is used to do an accuracy assessment. And also used Google Earth Pro to check ground truth & Survey Department maps to check the validity.

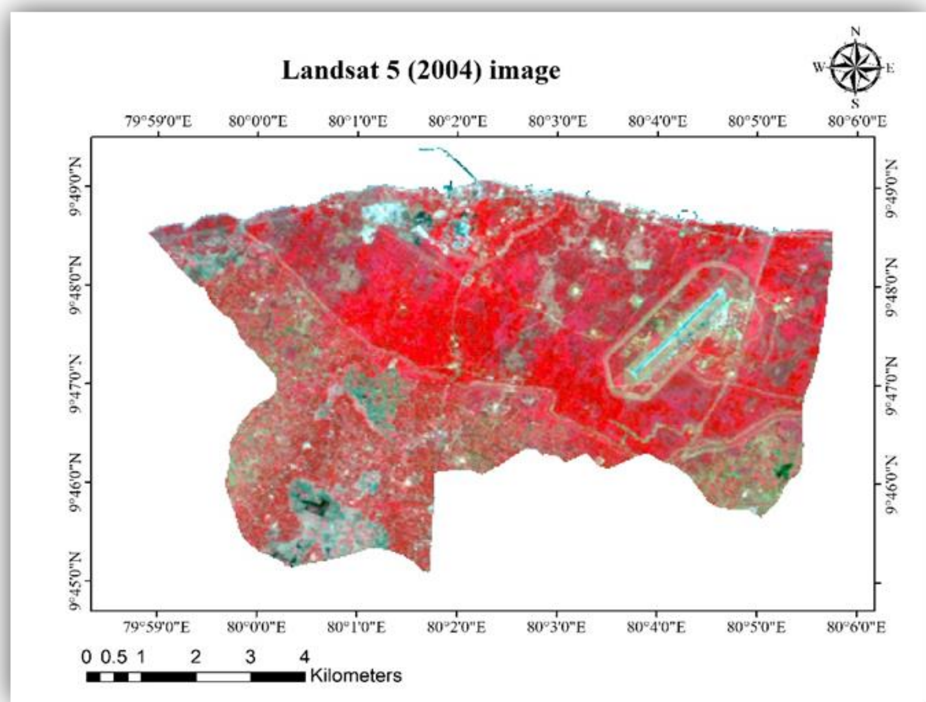

Figure 2: FCC Map Visualization of Landsat 5 (2004)

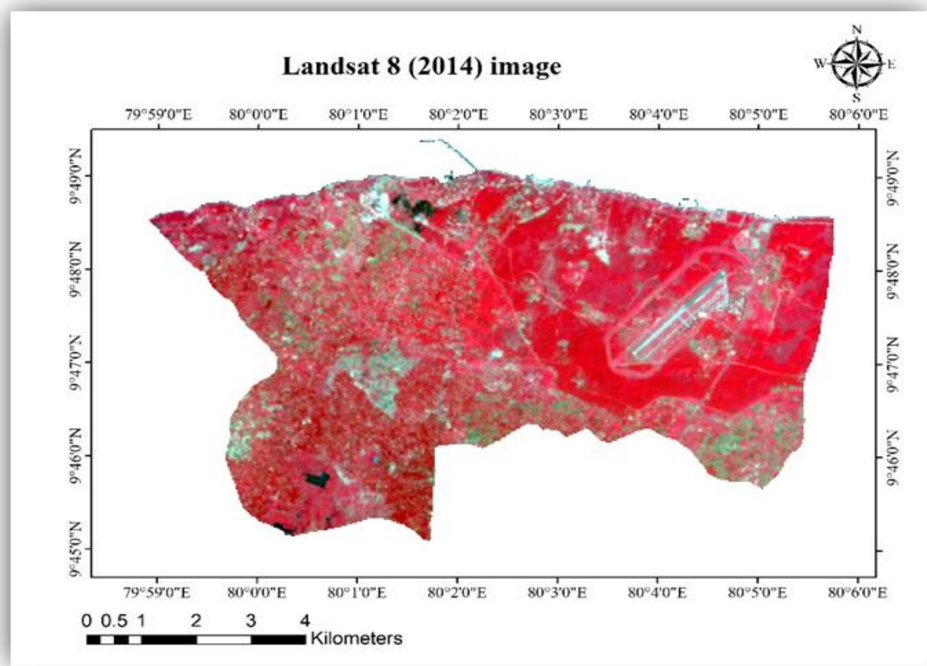

Figure 3: FCC Map Visualization of Landsat 8 (2014).

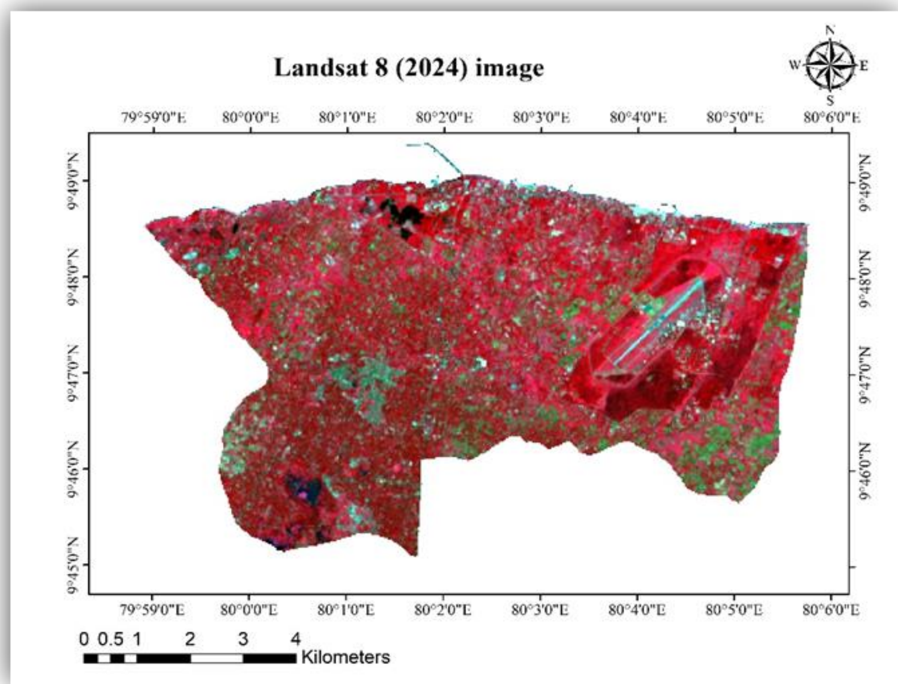

Figure 4: FCC Map Visualization of Landsat 8 (2024)

3.4 Land Use Land Cover Change Assessment: The LULC change assessment process involves systematic analysis of the land use and land cover changes over time. The aim is to identify, quantify, and understand patterns, drivers and causes of land use change (Singh, 1989). According to McLeod and Congleton (1998), it involves various steps, including data pre-processing, change detection, accuracy assessment and determining the area extent and spatial pattern (Congalton & Green, 2009**)**. It is also important for decision-making. QGIS, a widely used geographic information system (GIS), provides a platform for land use change simulations using the MOLUSCE (Modules for Land Use Change Simulations) extension. MOLUSCE is used to identify land use/cover changes over time. It also provides tools and services designed specifically for analysis. Using classified maps of 2004, 2014, and 2024, we generate change maps and tables on QGIS MOLUSCE. First, generate the 2004-2014 change map and tables, and then generate the 2014-2024 change map and tables. & also, it generates a transition matrix. So, after that, assess the changes. (Singh, 1989)

3.5 Future Prediction of LULC changes: Future Predictions of LULC help us in different in the identification of sustainable development opportunities, future challenges and prioritization of achieving long-term environmental resilience and sustainability. This project uses Transition Potential Modelling to simulate the future prediction & Artificial Neural Network (Multi-layer Perceptron) method of detecting LULC transitions Transition potential modelling is a method to predict possible transitions between states in a system. The Cellular Automata algorithm was then used to generate future prediction maps. Cellular Automata (CA) algorithms are an interesting way to model systems with simple rules that can lead to complex behaviours.

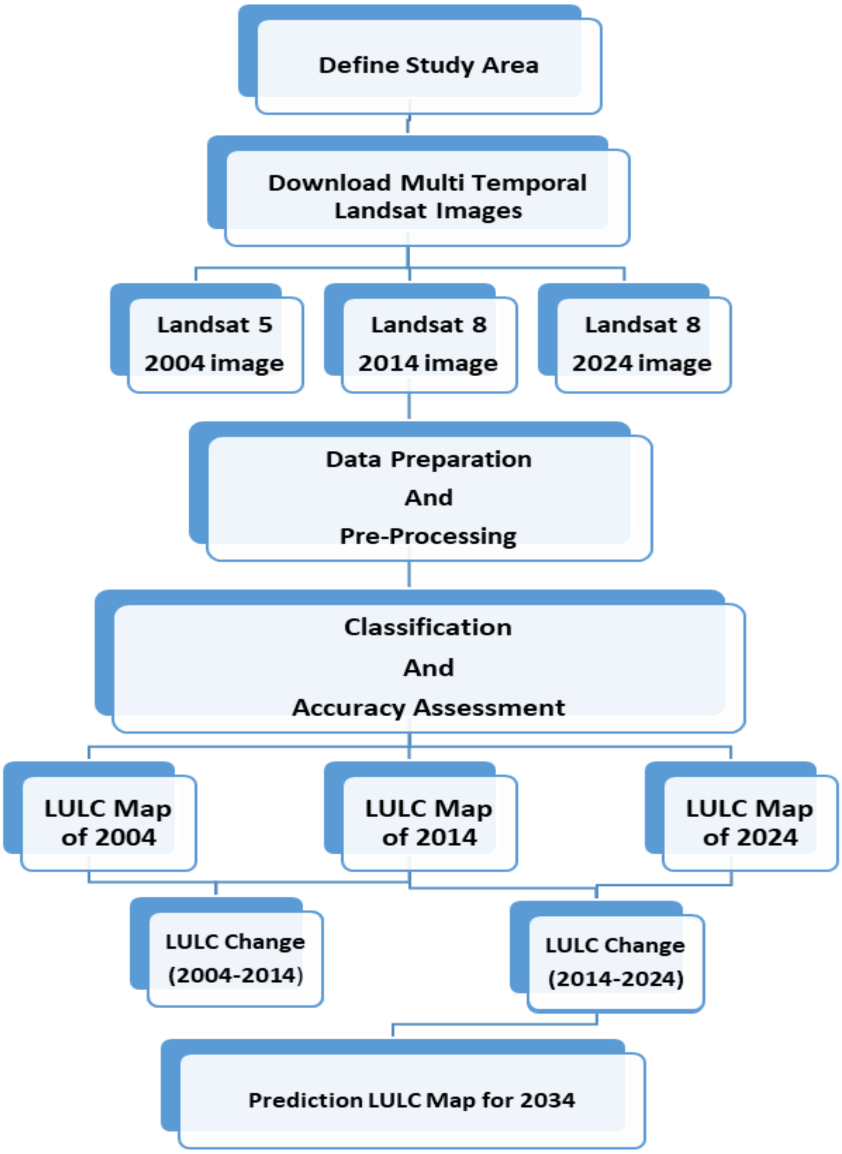

Figure 5: Methodology Flowchart

4. Results & Discussion:

After the analysis and classification of the LULC we get some interesting and variety of results as follows.

4.1. LULC change and Accuracy Assessment of LULC in 2004:

The results of the 2004 Land Use Land Cover Classifier (LULC) show that the diversity of land cover in the study area (Figure 6) (Sharma et al, 2018). Forest area becomes the dominant land cover, accounting for 42% of the total land area (Table 2) (McGarigal & Marks, 1995). Indicating that forests, meadows and other areas with scrubs. The percentage of built-up areas representing urban infrastructure is, 30.53%, which reflects the habitat and environment of the population. Agricultural land, including Agricultural land, accounts for 14.12% of the land area, which emphasizes the importance of agriculture in that region. Bare land accounts for 12.48% of the area, which means areas with little vegetation or degraded soil. Existing water, including ponds and reservoirs, except for a relatively small percentage of 0.87%, which indicates the presence of aquatic ecosystems in the study area. The Classification accuracy is 89% of kappa accuracy (Table 3) & provides valuable information on land cover classification and composition and facilitates informed decisions about environmental management, urban planning and conservation measures.

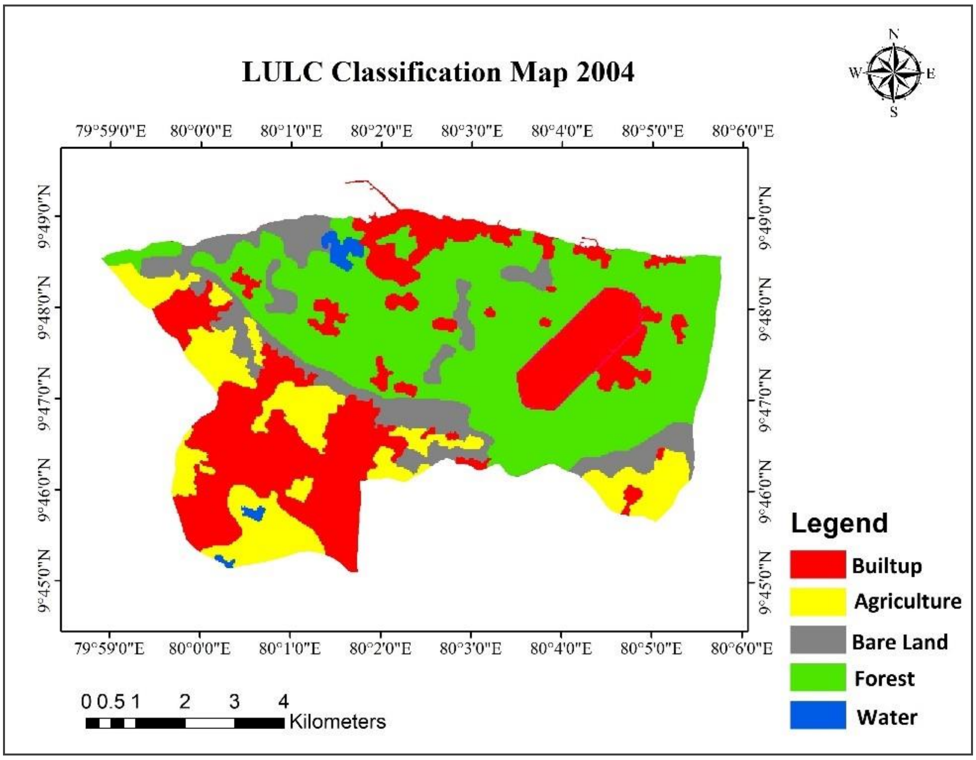

Figure 6: Land Use Land Cover map of Tellippalai, Sri Lanka (2004)

4.2 LULC change and Accuracy Assessment of LULC in 2014:

In the comparisons with 2004 the built-up area is massively increased in the year of 2014. It takes almost 40.74%. It shows the rapid growth of urbanization. Agricultural land has also expanded, accounting for 18.56% of the land surface, indicating the intensification of agricultural activities and changes in land use as a result of population demand and increasing agricultural practices. But the forest cover decreased to 28.24%. Bare land is still relatively stable at 11.55%. While the coverage of the water area has less change (0.89%). (Table 4). The classification accuracy is 91% of kappa accuracy (Table 5) and provides valuable information on land cover classification. What proportion of land use is converted to other land use categories from 2004 to 2014, is shown in (Table 6).

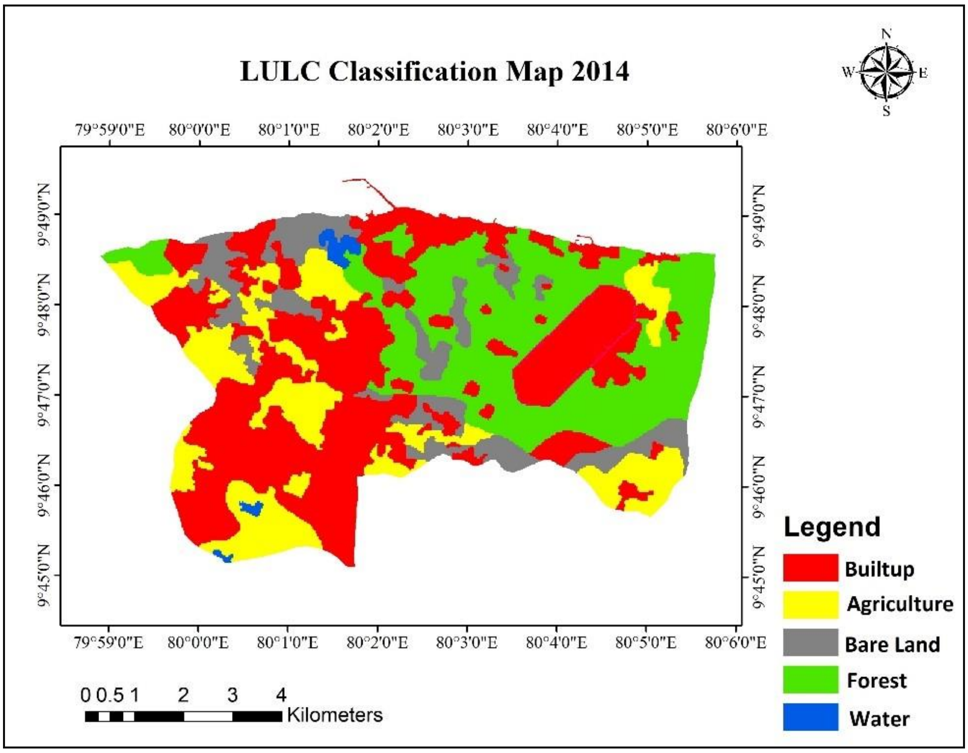

Figure 7: Land Use Land Cover map of Tellippalai, Sri Lanka (2014)

4.3 LULC change and Accuracy Assessment of LULC in 2024: In 2024, land use and land cover changed significantly as compared to 2004 and 2014. The built-up area takes up almost 54.50% of the total area. It shows the massive changes in LULC. Agriculture land is also increased by 26.17% of the total land cover. But the forest cover decreased to 13.74%. Bare land decreased to 4.71%. While the coverage of water areas little bit changes at 0.87% (Table 7). This information has a kappa accuracy of 89% (Table 8) and provides valuable information on land cover classification. What proportion of land use is converted to other land use categories from 2014 to 2024, as shown in (Table 9).

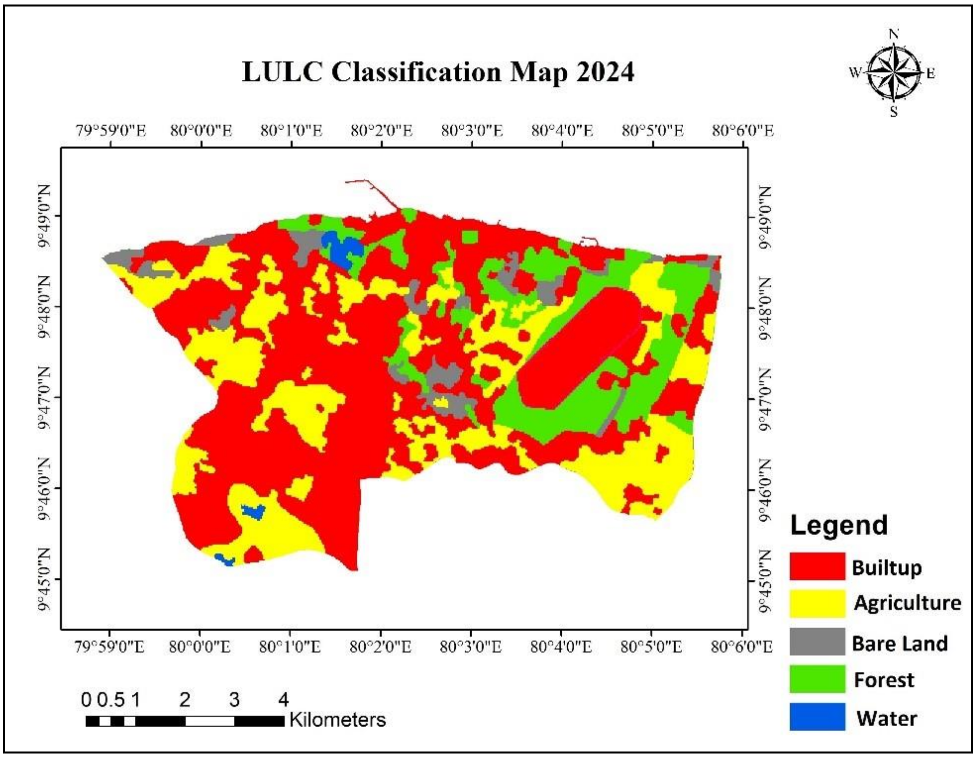

Figure 8: Land Use Land Cover map of Tellippalai, Sri Lanka (2024)

4.4 LULC prediction in 2034: The results of the predictive year 2034 land use and land cover classification show significant changes in the land use structure compared to previous years (Lambin, 1999). Built-up areas increased significantly, 54.3% of the total area. Agricultural land has also expanded, 32.75% of the land surface. But the Forest cover decreased to 6.76%. Bare land decreased to 0.27 %. While the coverage of water areas is constant at 0.87% (Table 10). This information has a predictive accuracy of 78%. What proportion of land use is converted to other land use categories in 2024 to the predicted year 2034, shown in (Table 11).

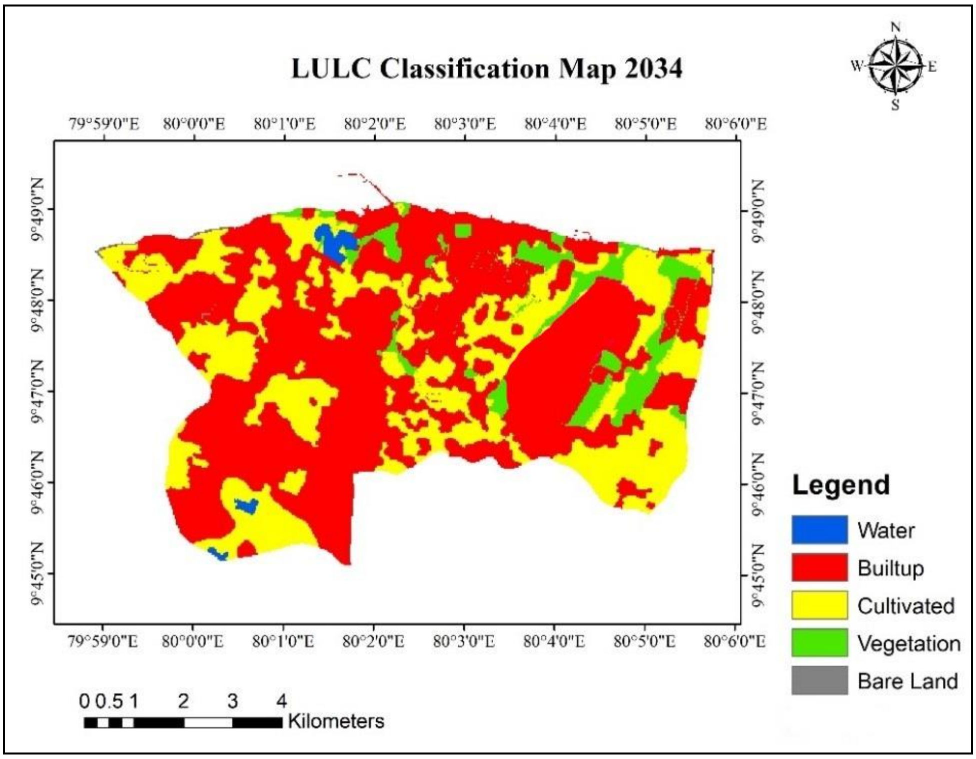

Figure 9: Land Use Land Cover Future Prediction map of Tellippalai, Sri Lanka (2034)

4.5 Temporal Change in Land Use & Land Cover: After getting some results from different techniques we make a temporal analysis to identify the changes in LULC statistically (Turner et al., 2007). (Figure 10) shows the relative changes for the time periods of 2004-2014, 2014-2024, and 2024 to the predicted year 2034. It shows built-up areas and agricultural areas have plus changes (Liu and Yang, 2015), which means these LULC class areas increased. Forest & Bare lands minus changes, that means these LULC classes area decreased in this period. (Figure 11) shows the decadal changes in the land use percentage according to the study area. It shows built-up area and agricultural areas continuously increased and forest and bare lands decreased (Gibson et al., 2000). The water class shows almost the same area. As you have seen, 30 years later, in 2034, there is a clear change in the picture of the study area. By comparison, it shows the built-up areas changed from 35% to 59% (see Figure 11). And forest cover loses its area from 42% to 6% in these 30 years. (Turner et al., 1995).

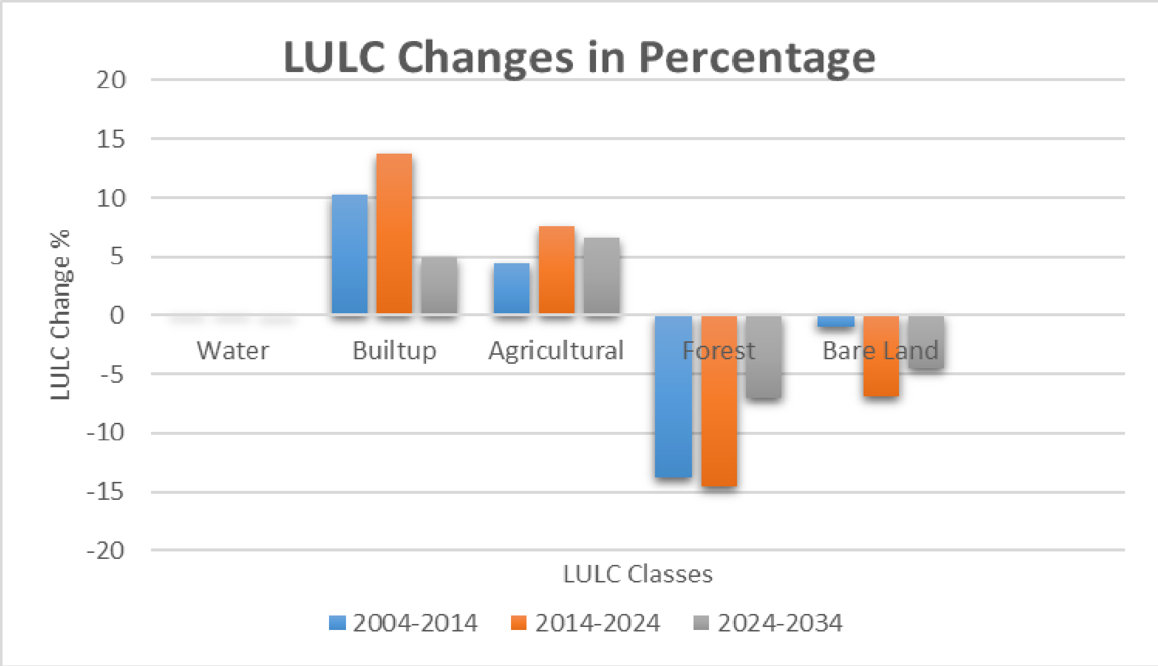

Figure 10: Relative change in different Land use & Land cover classes in Tellippalai, Sri Lanka (2004 to 2034).

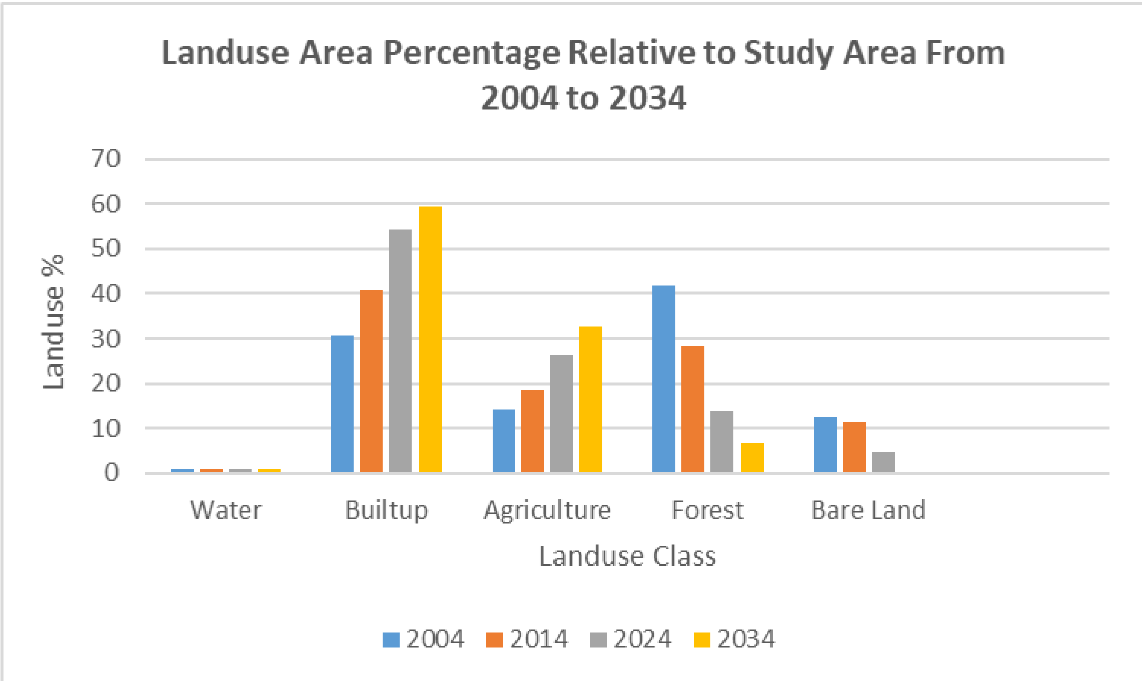

Figure 11: Area Percentages of different LULC classes in Tellippalai, Sri Lanka (2004 to 2034).

5. Conclusion & Recommendations:

5.1 Conclusion:

This study signifies LULC change and future prediction in Tellippalai DS area (Valikamam North) is a regional division of Jaffna district in Sri Lanka. The integration of remote sensing and GIS gives different results at different decadal times. Here we have collected Landsat 5 and 8 datasets in 2004, 2014, and 2024. After analysis of the results, we have found the built-up area increasing and the forest area decreasing every year. During this time, there was also a growth of approximately 6% to 8% in the agricultural area related to the study area, while bare lands saw a decrease. However, there have been very few notable alterations in the Water category. The significant changes are documented in the domain of built-up areas and agricultural areas. In 2004, the built-up area was calculated as 25.35 percent; in 2014 it was 35.57 percent; and in 2024 it rose to 49.33 percent and also 54.3 percent for the forecast year 2034. The percentage of agricultural land was 14.12, 18.56, and 26.17 in 2004, 2014, and 2024, respectively, and also 32.75 percent for the predicted year 2034. It demonstrates a consistent rise. This rise is the most likely cause for the reduction in forest area. Whereas in 2004, 2014, and 2024, the proportion of land covered by forests was 42.00, 28.27, and 13.74, respectively, it is forecasted as 6.76% in 2034. Land cover and usage under the categories of barren land & water bodies showed very negligible variation over that period.

In addition, the project demonstrated the importance of LULC maps and analyses for understanding environmental changes, monitoring ecosystem health, and decision-making processes for urban planning and social and related implications for economic development. The findings of this project can form the basis for the development of sustainable land use plans, using targeted reserves for conservation use of the region, promoting land resilience and enhancing environmental sustainability, and continuously monitoring and assessing land cover change.

This study in general reflects the long-term LULC change detection and monitoring. In this study, an ANN with the integration of remote sensing and GIS is applied to model LULC change in order to offer a detailed evaluation of present-day (LULC) as well as forecasting future changes. This informative and proactive land management will be able to make sustainable decisions based on the region, which can also happen in here.

5.2 Recommendation

Based on the results of this project, a few recommendations can be offered to inform future studies. Gather new satellite and ground-truth data to enhance the accuracy of LULC mapping and make it more reliable. Use high-resolution imagery and advanced remote sensing methods to take the small spatial changes of these land cover types under consideration in order to better understand how LULC varies. Application of remote sensing and GIS techniques showed that land use/land cover practices had changed significantly in the study regions between two decades. Changes in LULC result in alterations in the arrangement and makeup of the landscape, which were assessed through the measurement of landscape metrics.

Furthermore, it will aid in evaluating the growth rate of the Built-up areas & agricultural areas and support in the planning, and development of the Tellippalai DS area. Use some other models to predict future changes & compare each other for better results.

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7. Annexures

Class Name	Area in Ha	Area in %
Water	53.01	0.87
Built-up	1850.04	30.53
Agriculture	855.45	14.12
Forest	2544.84	42.00
Bare Land	756.36	12.48
Total	6059.7	100.00

Table 2. Area under different Land use Land cover Categories in 2004

ClassValue	Water	Built-up	Agriculture	Forest	Bare Land	Total	U_Accuracy	Kappa
Water	3	0	0	0	0	3	1	0
Built-up	0	21	2	1	0	24	0.869565	0
Agriculture	0	1	15	0	0	16	0.9375	0
Forest	0	1	0	40	2	43	0.928571	0
Bare Land	0	0	1	0	12	13	0.923077	0
Total	3	23	18	41	14	100	0	0
P_Accuracy	1	0.909091	0.833333	0.975	0.857143	0	0.92	0
Kappa	0	0	0	0	0	0	0	0.89077

Table 3. Accuracy assessment of LULC classification 2004

Class Name	Area in Ha	Area in %
Water	54.04	0.89
Builtup	2468.08	40.74
Agriculture	1124.72	18.56
Forest	1712.97	28.24
Bare Land	700.02	11.55
Total	**6059.7**	**100.00**

Table 4. Area under different land use Land cover Categories in 2014

ClassValue	Water	Built-up	Agriculture	Forest	Bare Land	Total	U_Accuracy	Kappa
Water	4	0	0	0	0	4	1	0
Built-up	0	32	1	0	0	33	0.969697	0
Agriculture	0	1	15	0	1	17	0.882353	0
Forest	0	2	0	35	0	37	0.944444	0
Bare Land	0	0	0	1	7	8	0.875	0
Total	4	35	16	36	8	100	0	0
P_Accuracy	1	0.914286	0.9375	0.971429	0.875	0	0.94	0
Kappa	0	0	0	0	0	0	0	0.916932

Table 5. Accuracy assessment of LULC classification in 2014

	Water	Built-up	Agriculture	Forest	Bare Land
Water	99.87%	0.00%	0.09%	0.04%	0.00%
Built-up	0.00%	99.61%	0.00%	0.39%	0.00%
Agriculture	0.00%	2.57%	97.43%	0.00%	0.00%
Forest	0.00%	17.21%	9.26%	65.35%	8.18%
Bare Land	0.00%	21.80%	7.37%	5.81%	65.03%

Table 6. LULC Transition Metrix for 2004-2014

Class Name	Area in Ha	Area in %
Water	52.91	0.87
Built-up	3302.81	54.50
Agriculture	1585.8	26.17
Forest	8327.7	13.74
Bare Land	285.48	4.71
Total	**6059.7**	**100.00**

Table 7. Area under different land use Land cover Categories in 2024

Class Value	Water	Built-up	Agriculture	Forest	Bare Land	Total	U_Accuracy	Kappa
Water	5	0	0	0	0	5	1	0
Built-up	0	34	2	0	1	37	0.9166666	0
Agriculture	0	2	24	1	0	27	0.8846153	0
Forest	0	1	0	19	0	20	0.95	0
Bare Land	0	0	0	1	10	11	0.9090909	0
Total	5	37	26	21	11	100	0	0
P_Accuracy	1	0.91666	0.92	0.904761	0.90909	0	0.92	0
Kappa	0	0	0	0	0	0	0	0.89316

Table 8. Accuracy assessment of LULC classification in 2024

	Water	Built-up	Agriculture	Forest	Bare Land
Water	99.70%	0.00%	0.18	0.12%	0.00%
Built-up	0.00%	95.22%	1.37%	2.57%	0.84%
Agriculture	0.00%	13.55%	84.76%	1.21%	0.48%
Forest	0.00%	33.57%	18.63%	39.98%	7.82%
Bare Land	0.00%	29.89%	40.54%	11.28%	18.30%

Table 9. LULC Transition Metrix for 2014-2024

Class Name	Area in Ha	Area in %
Water	51.74	0.85
Built-up	3595.86	59.34
Agricultural	1985.77	32.77
Forest	4098.6	6.76
Bare Land	16.47	0.27
Total	**6059.7**	**100.00**

Table 10. Area under different Land use Land cover categories in predictive year

	Water	Built-up	Agriculture	Forest	Bare land
Water	99.49%	0.17%	0.34%	0.00%	0.00%
Built-up	0.00%	99.99%	0.01%	0.00%	0.00%
Agriculture	0.00%	0.17%	99.83%	0.00%	0.00%
Forest	0.00%	30.24%	20.54%	49.22%	0.00%
Bare Land	0.00%	14.12%	80.11%	0.00%	5.77%

Table 11. LULC Transition Metrix for 2024-2034