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"Geospatial Analysis of Land Use Land Cover Change Dynamics for Sustainable Urban Planning: A Case Study of Amaravati Region, Guntur, Andhra Pradesh, India"

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Abstract
Land use and land cover (LULC) are fundamental components of the Earth's surface, representing the environment and influencing the lives of both human and natural communities, as well as their mutual interactions. Following the announcement of Amaravati as the capital city of the newly formed state of Andhra Pradesh, Land use and land cover (LULC) in the Amaravati region have undergone profound changes over the past decade, primarily due to anthropogenic activities resulting from urbanization. This study aims to identify and analyze general trends in Land Use/Land Cover Change (LULCC) that have occurred in the study area over a 12-year period, specifically from 2009 to 2021, using geospatial tools such as Remote Sensing and GIS techniques in the Amaravati region of Guntur, Andhra Pradesh, India. The study used multi-spectral satellite datasets for five years: Landsat 5-TM (2009) and Landsat 8-OLI (2015, 2017, 2019, and 2021). These images were pre-processed using Erdas Imagine 15, and five major LULC classes from Anderson's classification Agriculture Land, Bare Land, Built-up Land, Vegetation, and Water Bodies were delineated by collecting spectral signatures and classified using the Maximum Likelihood method under the Supervised Image Classification Technique in the ArcGIS 10.5 platform. The study revealed that the percentage of agricultural lands decreased from 25.02% in 2009 to 44.08% in 2015 and then rose to 5.01% in 2021. Between 2009 and 2021, the percentage of built-up land increased from 5.12% to 11.70%. Throughout the study, vegetation covers steadily declined from 2009 to 2019 but started growing again in 2021. This results from abandoned land being used for urban development, which was subsequently reforested with open scrub. This had an impact on local farming methods. As a result, the spatiotemporal and prospective results of the LULC simulation could help policymakers examine changes in LULC intensity and the impact of socioeconomic factors, as well as support plans for sustainable urban development and environmental preservation of the city.

Keywords: Land Use Land Cover, LULC classes, Remote Sensing and GIS, Spectral signatures, Maximum Likelihood Classifier, Supervised Image Classification, urbanization.

1. Introduction

Land use and land cover (LULC) are fundamental components of the Earth's surface, representing the environment and influencing the lives of both human and natural communities, as well as their mutual interaction **[1]**. Land use refers to the human activities and practices that occur on the land, including agriculture, urbanization, forestry, and infrastructure development. Land cover refers to the physical characteristics of the Earth's surface, including forests, water

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bodies, urban areas, and bare lands. The earth's surface has undergone unprecedented anthropogenic changes, resulting in sizeable worldwide land use and cover changes [2].

Changes in LULC have far-reaching consequences for ecosystems, biodiversity, climate, and overall environmental sustainability. Land use and land cover change (LULCC) results from complex interactions between anthropogenic and environmental factors, as demonstrated by the findings of many researchers worldwide [3]. By examining past and present patterns of land use and land cover and detecting changes over time, researchers can identify trends, drivers, and potential future scenarios. This knowledge is invaluable for sustainable land management, conservation planning, disaster risk assessment, and climate change mitigation and adaptation strategies. Various natural and socioeconomic factors, as well as human actions, influence the use and coverage of land in a particular location over time and space. Therefore, accurate land use and cover information is crucial for making informed decisions in selecting, planning, and implementing land use strategies.

These studies often employ advanced technologies, such as remote sensing (RS) and geographical information systems (GIS). Integrating these cutting-edge tools with traditional ecological surveys provides a comprehensive understanding of complex landscape dynamics in a study area [4]. Conversely, GIS provides a versatile framework for gathering, storing, presenting, and analyzing digital data required for change detection [5]. RS and GIS techniques may successfully monitor and anticipate LULC changes by analyzing previous remotely sensed data [6][7]. The significance of remote sensing and GIS in land use land cover and change detection studies lies in their ability to provide large-scale, accurate, and timely information, enabling effective decision-making and monitoring of our changing landscape and environment.

Literature offers several approaches for anticipating LULC changes. Methods vary depending on aim, methodology, geography, assumptions, and data type [8]. Choosing a suitable classification system, selecting training samples, pre-processing the image, extracting features, selecting appropriate classification approaches, performing post-classification processing, and assessing accuracy are some critical steps in image classification [9]. Enhancing land cover classification accuracy requires the use of an appropriate classifier [10]. The maximum likelihood classification (MLC) method, a supervised image classification technique, is employed in the present study to classify satellite images. MLC is a traditional classification method, yet it remains the most extensively used parametric classification algorithm due to its theoretical foundation and widespread availability in many commercial and free processing applications. It is simply a pixel-based classifier algorithm that requires a significant number of representative training samples for each class to accurately estimate the mean vector and covariance matrix required for the classification method [11][12][13]. These training zones are then statistically characterized and presented to the computer for analysis. The computer algorithm then divides the pixels of the entire scene into the spectral class that appears to be the most similar. A detailed description of MLC is explained in many books [14][15][16].

Cities are intricate systems that blend the built, environmental, and social elements. Our urban problems require interdisciplinary cooperation and coordinated strategies to solve. Urbanization and growth have long been considered crucial indicators of a nation's economic development. Cities have increased substantially in size over recent decades, accompanied by a corresponding rise in population [17]. Almost 54% of the world's population lived in urban areas in 2014 (up from 30% in 1954). World Population Prospects (The 2014 Revision) predicts that by 2050, when the urban population will have grown by 2.5 billion to a total of about 7.6 billion, this percentage will rise to 66%. This has significantly impacted the geology and geomorphology of Earth's shallow geosphere and will continue to do so. Knowing the characteristics and geometries of the geological considerations is crucial for intelligently and sustainably planning infrastructure and for responsibly reusing urban areas to support economic and social growth [18]. Urbanization and population growth increase the need for

infrastructure, resources, and services. A global imperative is to guarantee the sustainability of these urban settings [19].
The land cover and landscape patterns of the area in question have undergone major changes due to urbanization. It has had numerous negative impacts on the physical environment, including the disappearance of farmland, depletion of ground and surface water, alteration of landforms, flooding, and landslides. The daily increase in population has necessitated the implementation of effective urban planning to ensure the long-term environmental stability of a region. Both surface and groundwater are contaminated by the rapid expansion of urbanization and poorly planned, unregulated industrial operations [20].

1.1 Motivation and Research Gap:
The motivation for the present research work stems from the idea of selecting the Amaravati region of Guntur, Andhra Pradesh, as the study area. This region was proposed as the capital city of the newly formed state of Andhra Pradesh in India in 2014. The announcement of this region as a capital city poses a challenge for policymakers, as it is located in the agricultural floodplain region of the Krishna River. The Amaravati region was once barren land, but it was transformed into agricultural land with the advancement of irrigation schemes in the state of Andhra Pradesh. As this region was predominantly agricultural land at the time of the announcement, making it the capital city of Andhra Pradesh, it is challenging for the Andhra Pradesh government to develop the city sustainably. However, analyzing the region's land use and land cover patterns over a particular period enhances policymakers' and stakeholders' ability to plan sustainable urban planning, considering socio-economic and environmental factors. By examining past and present patterns of land use and land cover and detecting changes over time, researchers can identify trends, drivers, and potential future scenarios. This knowledge is invaluable for sustainable land management, conservation planning, disaster risk assessment, and climate change mitigation and adaptation strategies.
Moreover, these studies often employ advanced geospatial technologies, such as GIS and remote sensing. Integrating these cutting-edge tools with traditional ecological surveys provides a comprehensive understanding of complex landscape dynamics [21]. Urbanization has played a significant role in shaping our current land-use regimes. This process often involves converting non-urban areas into urban spaces, known as urban sprawl. Unfortunately, this expansion frequently encroaches upon productive agricultural land and vital forests, which cannot withstand the force of urban growth. This growth, a clear sign of urbanization and development, has notable effects on a region's natural earth system [22][23]. Various natural and socioeconomic factors, as well as human actions, influence the use and coverage of land in a particular location over time and space. Accurate information about land use is crucial for making informed decisions in selecting, planning, and implementing land use strategies [24]. This data is essential for meeting the increasing needs and welfare demands of humans and facilitating the monitoring of land-use changes due to population growth. Gaining Spatio-temporal data on land use and land cover change detection is crucial for improving decision-making and enhancing our understanding of the connections between human activities and the natural world. This data plays a vital role in comprehending how human actions impact the environment, leading to more effective decision-making and management strategies [25]. Multi-spectral satellite image classification has proven to be a practical application in the following areas: monitoring changes in ecosystem conditions [26][27], land cover maps [28][29][30], urban expansion [31][32], forest change [33][34][35].
The data coverage, data ages, and atmospheric noises in the data have become a challenge in the present study. In this context, this paper presents results established using available open-source data and adopts the results using different datasets from LANDSAT 8 OLI satellite imageries.

1.2 Statement of the problem:

Amaravati region, the northern part of the Guntur district, Andhra Pradesh, has witnessed remarkable changes such as significant building constructions, road networks, and conversion of agricultural land into bare land and vegetation (scrub) over the past ten years. Due to the rapid rise in land consumption and changes in land use and cover, mapping and evaluating these changes were not attempted. Therefore, the purpose of this study was to utilize satellite imagery and GIS-based techniques to identify and assess broad patterns in LULC changes that have occurred in the study area over 12 years. In this context, satellite imagery for the years 2009, 2015, 2017, 2019, and 2021 was analyzed, and land use and land cover classification was performed. This further helped in studying the temporal changes within the area.

1.3 Aim of the Study:

This study aims to identify and analyze general Land Use/Land Cover Change (LULCC) trends in the study area over 12 years (2009, 2015, 2017, 2019, and 2021) using geospatial tools such as remote sensing and GIS-based tools.

2. Study Area

The present study area, the Amaravati region, is located in the north-central part of Guntur District, Andhra Pradesh. It lies within longitude $80^0$24’10” E to $80^0$37’10’’E and latitude $16^0$23’N to $16^0$36’ N. It is located along the southern bank of the River Krishna and has adverse lithological, geological, geomorphological, and natural resource characteristics, as well as a challenging climate. The study area focuses on the proposed capital city, Amaravati region, of the newly formed state of Andhra Pradesh in the year 2014, covering an area of 414 km^2 total of five mandals with about 40 villages of five mandals, namely Amaravati, Thulluru, Mangalagiri, Tadepalli, and Tadikonda (Figure 1). The study was demarcated from mosaicked toposheets adopted from the Survey of India (SOI) using the ArcGIS platform (Figure 2). The region's population was projected to be 1,060,818 as of the 2011 census and falls within tropical savanna climate features, characterized by both wet and dry conditions, with temperatures ranging from 15°C to 25°C in the summer and exceeding 40°C, with an average annual rainfall of 1,324 mm. The geomorphology of the study area is characterized by a peneplain encompassing the plain of the River Krishna, featuring 1st-order to 2nd-order drainage streams that exhibit parallel, sub-parallel, and dendritic patterns. The area is characterized by discontinuous hills and ridges in the east and west zones, with an average elevation of 65 meters above Mean Sea Level (MSL). The region's geology consists of alluvium, Charnockite Gneisses, Khondalite Gneisses, and Migmatite Gneisses, All Part of the Eastern Ghats rocks within Andhra Pradesh.

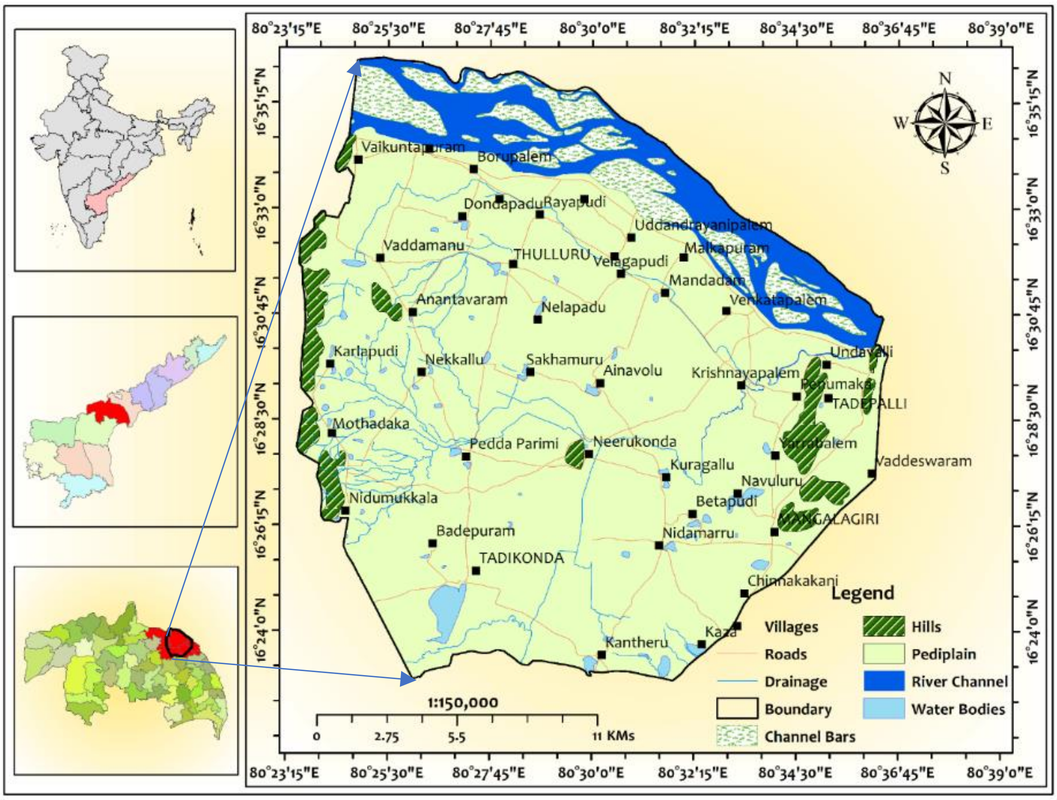


Figure 1: Location map of the Study Area

3. Materials and Methodology

This section discusses the details of the materials, such as satellite data, and the methodology adopted to enhance the present study. Unlike previous studies **[36][37],** the traditional methods of image classification, like the Maximum Likelihood Classification (MLC) of supervised image classification, were used for satellite image classification for LULC studies **[38].** The step-by-step procedure adopted to meet the successful evaluation of the research methodology is shown in the flowchart below in Figure 2. This includes the data used (multi-spectral satellite imageries), as well as data pre-processing steps such as image rectification, rescaling, resampling, composite band creation, and raster projection, as discussed in further detail in the sections below.

3.1 Data Type and Data Source

This study utilized multispectral satellite data for five years, specifically 2009, 2015, 2017, 2019, and 2021, during the months of March and April, with the closest acquisition dates. The satellite data collected were open-source, containing Landsat 5 Thematic Mapper (TM) and Landsat 8 Operational Land Imager (OLI) data downloaded from the USGS Earth Explorer (http://earthexplorer.usgs.gov/). The data sources, acquisition dates, resolutions, bands used, and sources are listed in Table 1. The natural-color composite satellite images of the above-mentioned periods are shown in Figure 3 below. This data is pre-processed using image enhancement techniques using ERDAS Imagine 15 software.

Table 1: Data Type and Data Source of LULC Studies

Satellite	Sensor	Acquisition Date	Bands Used	Spatial Resolution
Landsat 5	**TM**	04-04-2009	1,2,3,4,5,7	30m
Landsat 8	**OLI**	20-03-2015	1,2,3,4,5,6,7	30m
Landsat 8	**OLI**	16-04-2017	1,2,3,4,5,6,7	30m
Landsat 8	**OLI**	16-04-2019	1,2,3,4,5,6,7	30m
Landsat 8	**OLI**	21-03-2021	1,2,3,4,5,67	30m

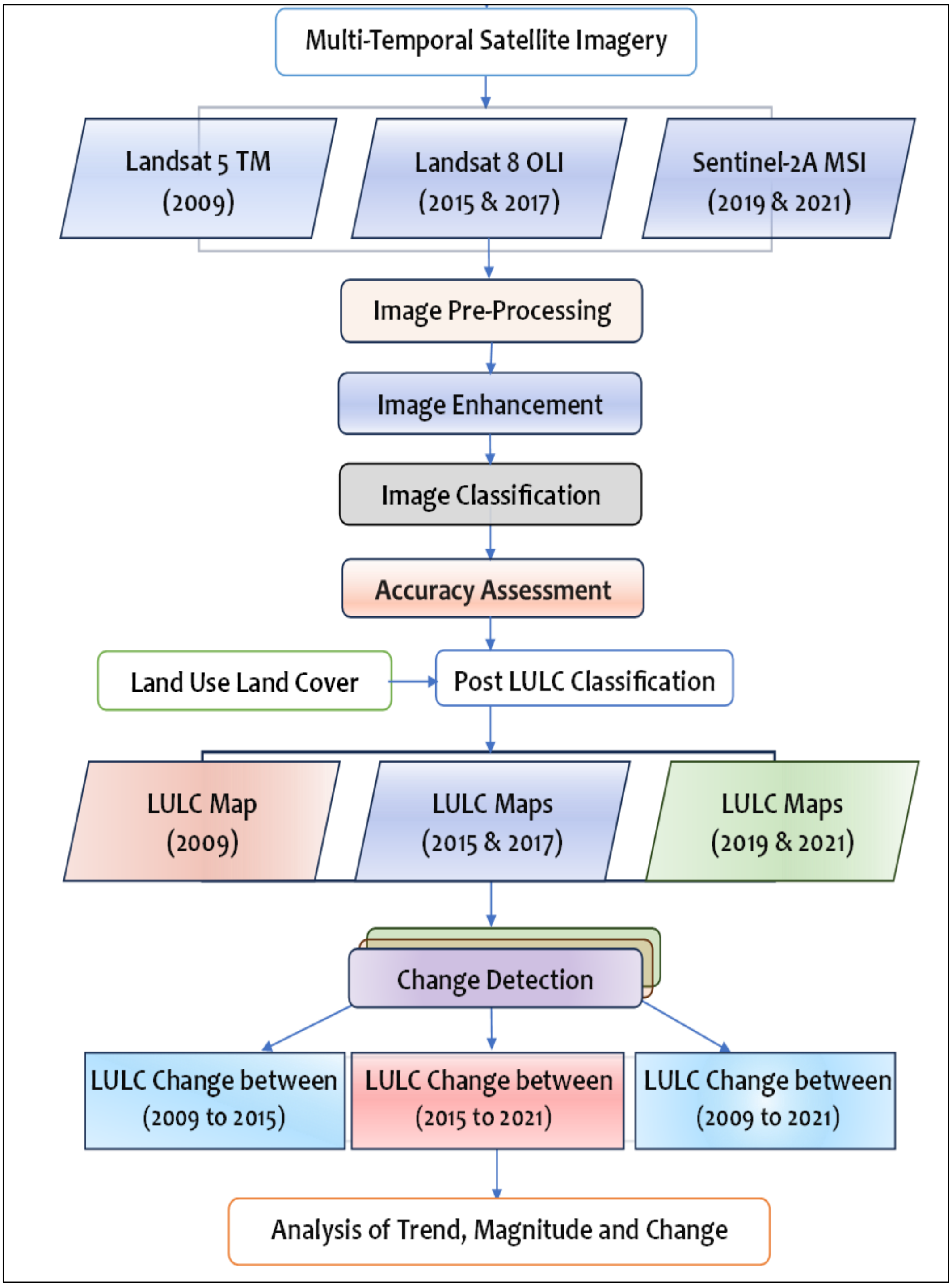


Figure 2: Flowchart of Methodology for the Present Study

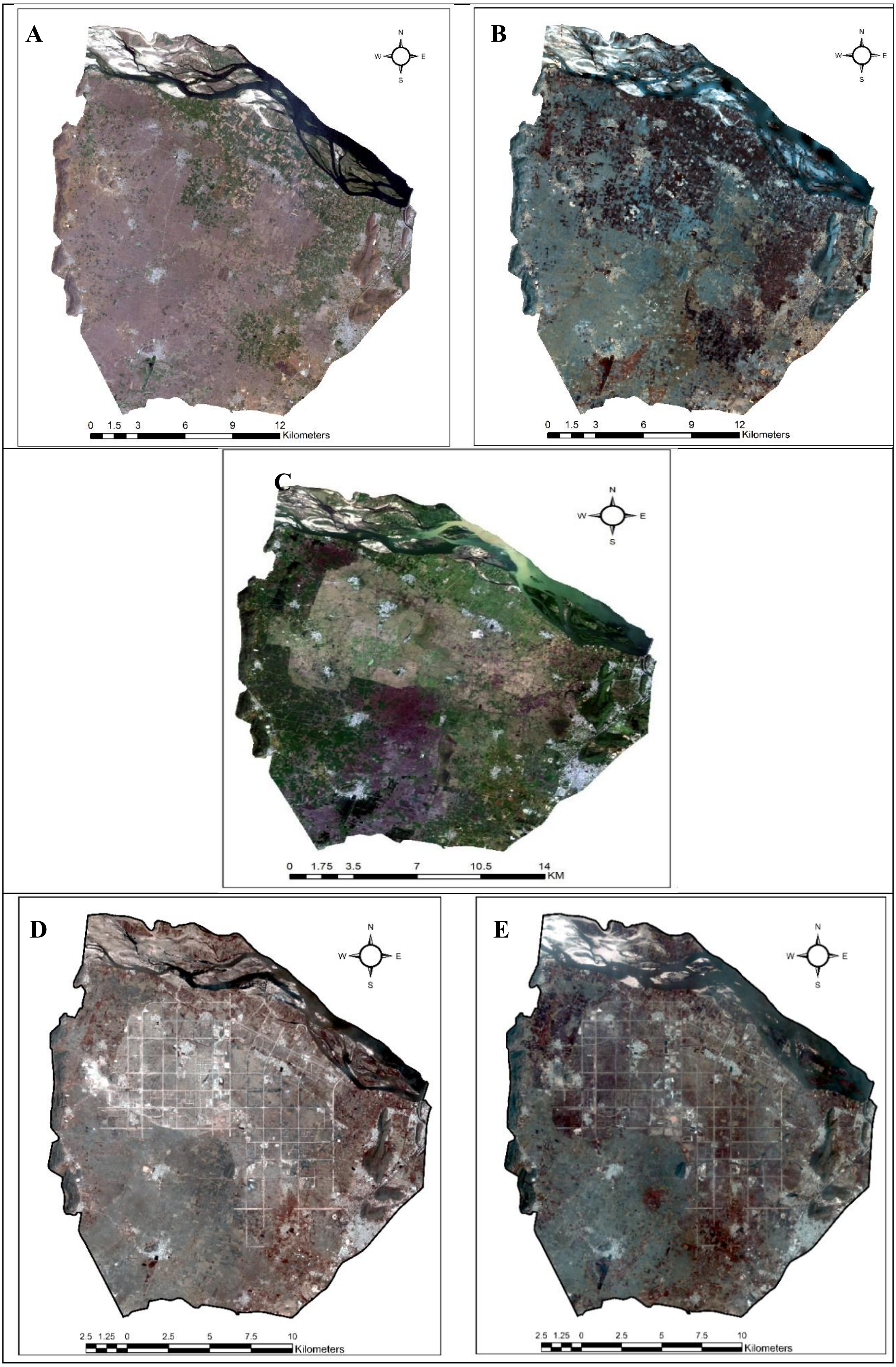


Figure 3: Satellite images of the Study area (A) 2009, Landsat-5 TM bands 3,2,1, (B), (C) (D) and (E) 2015, 2017, 2019, and 2021 Landsat-8 OLI bands 4,3,2 (RGB) Natural Colour Composite (NCC)

3.2 Data Processing and Software Used

All the visible and infrared bands of these satellite imageries are rescaled and resampled, and then composite bands are generated using tools in ArcGIS 10.5. These images were further processed, rectified, and projected to the Universal Transverse Mercator (UTM) Zone 44N, WGS 1984 datum. These images were rescaled and resampled using Erdas Imagine 2015 and ArcGIS 10.5 for Supervised Image classification and Microsoft Excel 2021 for statistical spatial analysis, accuracy assessment, and creating pie charts. The image classification procedure is discussed in the section below.

3.3 Image Classification

This study employed maximum likelihood classification (MLC), the most widely used parametric classifier. Using spectral properties and spatial patterns, the goal is to automatically categorize the image's pixels into various groups, assigning each pixel to a distinct class [39]. Choosing a suitable classification system, selecting training samples, pre-processing the image, extracting features, selecting appropriate classification approaches, performing post-classification processing, and assessing accuracy are some critical steps in image classification [40]. Five Level-I classifications were found using the given land use and land cover classification system [41]. Land used for agriculture, bare land, built-up land, vegetation, and bodies of water (Table 2). The maximum likelihood classifier (MLC) was the most widely used parametric classification algorithm in this study.
For this, the relevant signatures of each class mentioned above were collected using the ArcGIS platform, and these signatures were then classified under a supervised classification scheme using the Maximum Likelihood method in the ArcGIS platform. The five classes used indicate the properties as mentioned in Table 2 below.

Table 2: Land use and land cover classification scheme **(***after Anderson et al., 1976)*

Level I	Level II
Agriculture Land	Cropland, pasture, Flowering plantations, etc.
Bare Land	Bare exposed rocks and rocky hills, Strip mines, quarries, gravel pits, uncultivated agriculture lands,
Built-Up Land	Residential, Industrial; Commercial and services; Villages and Towns; Transportation, Communications, and Utilities; Mixed and other built-up land
Vegetation	Closed Forest land, open forest land, mixed forest; open scrub, aquatic flora.
Water Bodies	Rivers, Streams, and canals; Lakes and tanks

The images were assessed for accuracy after being successfully classified into these five classes, as discussed in the next section.

3.4 Accuracy Assessment

The accuracy assessment typically determines the quality of information retrieved from remotely sensed data [42]. The accuracy of the classification results is quantified by comparing them with reference data, commonly referred to as ground truth data. Accuracy assessment aims to evaluate how well the classified image represents the land cover or land use on the ground. An error matrix, which offers comprehensive information on the degree of agreement between the classification results and reference data, is a popular technique for assessing accuracy [43]. Furthermore, the error matrices were used to perform accuracy assessments, including the producer's accuracy, the user's accuracy, and the overall kappa coefficient. The kappa coefficient was calculated using equation (1) [44].

$$\textbf{Kappa Coefficient (T)} = \frac{\text{TS}\times\text{TCS})-\sum(\text{Column Total}\times\text{Row Total})}{TS^2-(\text{Column Total x Row Total}))}\times 100 \qquad \text{---- (1)}$$

where TS is the Total Number of Reference Pixels
TCS is the Total Number of Correctly Classified Pixels (Diagonal)

Overall accuracy and the kappa coefficient were interpreted and reported only if the results were above 80% or 85%. After a satisfactory accuracy assessment, the classified image was used for further analysis.

After successfully generating LULC maps from the satellite imageries, all classified imageries were assessed for accuracy using the Kappa statistical analysis [45]. The statistics and results discussed are presented in the following section.

4. Results and Discussions

This section presents image classification results and area statistics for each land use land cover (LULC) class. It analyzes changes in agriculture, built-up land, bare land, vegetation, and water bodies, which are crucial for understanding LULC dynamics. As the study area is the capital of the newly formed Andhra Pradesh, these insights help policymakers plan sustainable land use for urban development.

4.1 Land Use Land Cover Classification

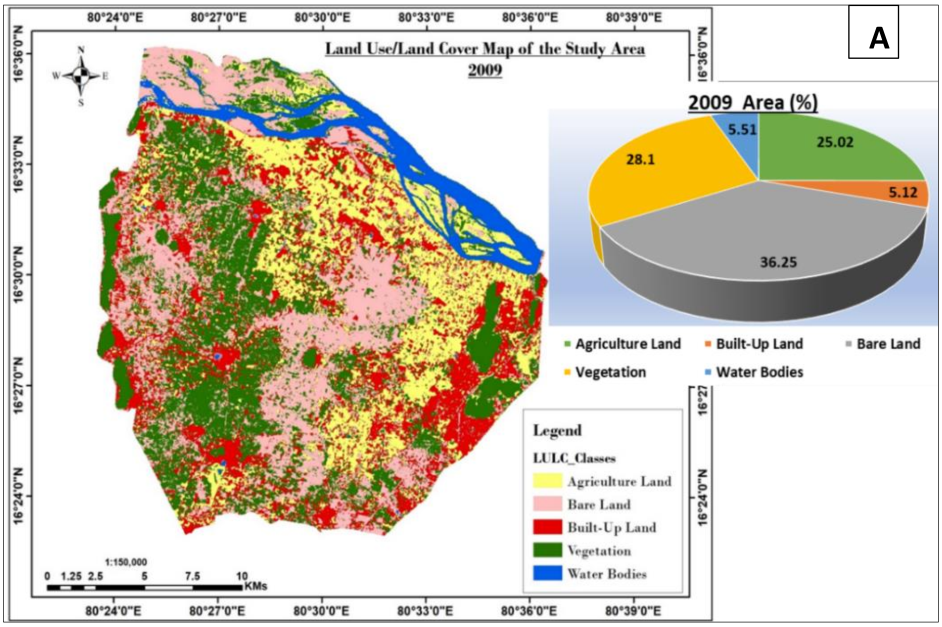
The connections between the LULC classes were determined and investigated, and LULC maps for 2009, 2015, 2017, 2019, and 2021 were developed, Figures 4A, 4B, 4C, 4D, 4E). Almost half of the current study area was used for agriculture within the rural area. The main land use and cover classes identified during the study periods are agricultural land, built-up area, bare land, vegetation, and water bodies. Table 3 displays the mapping results of land use and land cover.

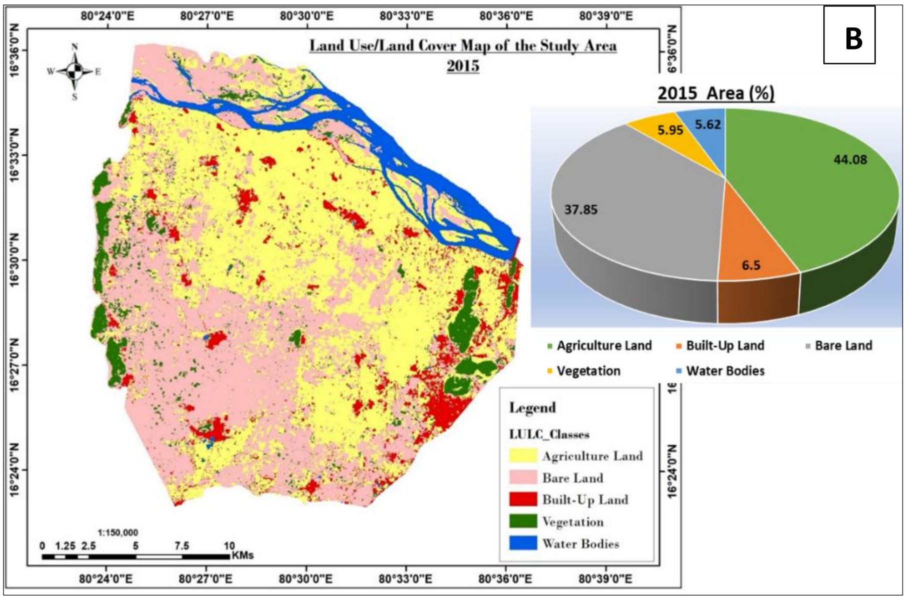
This research aimed to identify and analyze general trends in land-use/land-cover change (LULCC) in the Amaravati region over 12 years using Landsat Satellite Imagery and a GIS-based technique. The following are the study's key findings:

- ***Agricultural land:*** Agricultural land was primarily used to produce food and fodder. In 2009, agricultural land accounted for 25.02% of the total area. In 2015, approximately 44.08% of the total land area was used for agriculture. In 2017 and 2019, about 17.07% and 9.98% of the total area is under agriculture, respectively. In 2021, the area under the agriculture category is 4.98%.
- ***Built-up Land:*** The built-up land cover in 2009 was 5.12%. The total area covered by built-up land in 2015 and 2017 is 6.5% and 6.80% respectively. In 2019, the built-up area accounted for 11.44% of the total area. There was a positive change in built-up land over the past three years. In 2021, the percentage of built-up area was 11.90%.
- ***Bare Land:*** The Barren land was reported at 36.25% in 2009. The area covered by barren land in 2015 and 2017 was 37.85% and 48.85%, respectively. In 2019, the barren land was reported to be 44.33%, while in 2021, it decreased to 26.90%. In two years, there was a decrease in barren land of approximately 17.48%.
- ***Vegetation:*** The vegetation in the study area during 2009 and 2015 are reported as 28.1% and 5.95%, respectively. In 2017, the rate was 21.46%. This indicates a positive change in the vegetation of the study area. In 2019 and 2021, the percentages are 28.68% and 49.01%, respectively. In two years, there was a 20.33 increase in vegetation cover in the study area.
- ***Water bodies include rivers, streams, lakes, canals, ponds, and reservoirs, such as*** tanks. The percentage of water bodies in the region was 5.51% of the total area in 2009. The total area covered by water bodies in 2015 and 2017 was 5.62% and 5.79% respectively. The percentage of water bodies in 2019 was 5.59%, while in 2021, it increased to 7.31%.

Table 3: Land Use/Land Cover Distribution (2009, 2015, 2017, 2019, 2021)

Land Use/ Land Cover Classes	2009		2015		2017		2019		2021	
	Area (Sq km)	Area (%)	Area (Sq km)	Area (%)	Area (Sq km)	Area (%)	Area (Sq km)	Area (%)	Area (Sq km)	Area (%)
Agriculture Land	103.44	25.02	182.51	44.08	70.67	17.07	41.27	9.98	20.56	4.98
Built-Up Land	21.17	5.12	26.87	6.5	28.17	6.80	44.52	11.42	48.94	11.85
Bare Land	149.86	36.25	156.69	37.85	202.19	48.85	183.01	44.33	111.02	26.85
Vegetation	116.25	28.1	24.65	5.95	88.84	21.46	121.23	28.68	202.62	49.01
Water Bodies	22.84	5.51	23.25	5.62	23.97	5.79	23.12	5.59	30.23	7.31
Total	**413.56**		**413.97**		**413.84**		**413.15**		413.37	





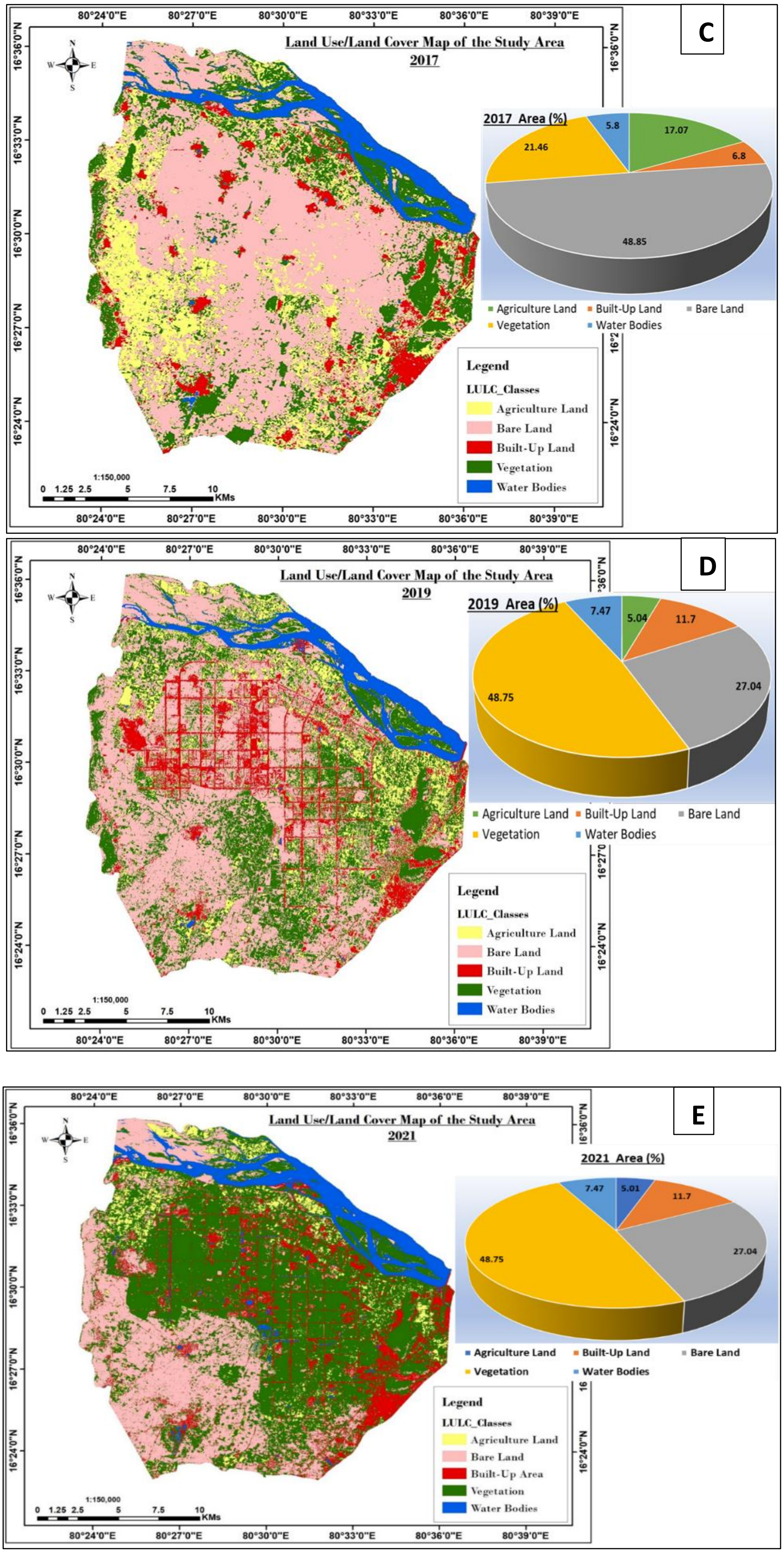


Figure 4: Land Use Land Cover Maps of the Study Area **(A)** 2009, (**B)** 2015, **(C)** 2017, **(D)** 2019, and **(E)** 2021

4.2 Accuracy Indices:

A high classification accuracy of about 80 to 85% is crucial for reliable land use change detection, environmental monitoring, and decision-making processes **[46]**. The accuracy of all five-time series classified maps was assessed in this study. Confusion matrices were used to evaluate classification accuracy using four metrics: user accuracy, overall accuracy, producer accuracy, and the Kappa statistics. The overall accuracies and kappa statistics for the LULC maps are shown in Table 4.

Table 4: Overall Accuracies and Kappa Statistics of Generated LULC Maps

S. No.	Period	Overall Accuracy (%)	Kappa Coefficients (%)
1	2009	84.68	80.18
2	2015	92.61	89.56
3	2017	90.38	87.15
4	2019	89.46	86.32
5	2021	91.23	87.96

4.3 LULC Change Dynamics

Upon successfully assessing the accuracy of classified images from different periods, one can generate change detection maps using the ArcGIS platform. Our results align with the findings of similar studies to understand the spatiotemporal dynamics of LULC changes [47][48][49]. The total area of each land cover class for the entire study was compared using five classified images from 2009, 2015, 2017, 2019, and 2021. The changes in area for different LULC classes are presented in tabular, pictorial, and map formats. From the critical findings mentioned above, the temporal changes between 2009 and 2015, 2015 and 2021, and 2009 and 2021 are illustrated in Figures 5A, 5B, and 5C, respectively. The comparison pie charts are presented in Figures 6A, 6B, and 6C, respectively. The major changes found during these periods are as follows.

- From 2009 to 2015, there was a 21% shift in agricultural practice, which drastically dropped to 27% during 2015. In 2019, agricultural activity decreased by 9.9% and further declined to 5% in 2021. This implies that the announcement of the capital region in Andhra Pradesh led to agricultural practices that contributed to land degradation and urbanization in the region.
- From 2009 to 2017, the average built-up area accounted for 6%, drastically increasing to 11% in 2016 and continuing until 2021. This indicates the shift in urbanization.
- Water bodies accounted for an average of 5.5% of the total area during 2009, 2015, 2017, and 2019. However, the water bodies in 2021 accounted for approximately 7.5%. This 2% increase is due to the construction of artificial canals between the Kondaveeti Vagu and Kattela Vagu within the capital region.
- In 2009 and 2015, the bare land area accounted for an average of 37%, whereas in 2017, it accounted for approximately 49%, indicating a shift from agricultural activity to urban clusters. The agricultural land was converted into bare land for further urban development in 2016. During 2019, bare land accounted for approximately 44.33% of the total, and there was an increase in the built-up area during this period. It reduces to 26.9% during 2021.
- The vegetation cover accounted for 28% in 2009, reduced to 5% in 2015, and then increased to 21%, 29%, and 49%, respectively. This indicates the reduction in 2015 due to urban expansion.
- From the above, it is inferred that between 2015 and 2021, there was a drastic decline in agricultural activity and a significant conversion of these lands into bare land. However, from 2019 to 2021, it was observed that there was an increase in built-up areas, water bodies, and

vegetation and a decrease in bare land. The field observations confirmed that the land acquired for urban development was left undeveloped, resulting in the growth of open scrub.

- These changes resulted in the transformation of agricultural land into bare land and built-up areas, further leading to the growth of open scrub vegetation that lacks agricultural practices.
- Figure 4D (2019) and Figure 4E (2021) illustrate the changes within the Amaravati region, showcasing the development of built-up areas, such as road networks, and the transformation of bare land into dense vegetation cover.
- This, therefore, suggests that the rate at which the agricultural activity within the study area reduced by 40%, the shift of built-up area by 5%, the reduction of bare land by 20%, and the shift of these lands towards vegetal matter (open scrub) by 22% and a little increase of water bodies by 2%. The vegetation and water bodies decreased by 42% and 1.85% respectively.

The LULC changes between the periods 2009-2015, 2015-2017, 2017-2019, 2019-2021, and 2015-2021 are shown in Table 5.

Table 5: Land Use Land Cover Changes of the Study Area

Land Use/ Land Cover Classes	2009 to 2015		2015 to 2017		2017 to 2019		2019 to 2021		2015 to 2021	
	Area (Sq. Km.)	Area (%)	Area (Sq. Km.)	Area (%)	Area (Sq. Km.)	Area (%)	Area (Sq. Km.)	Area (%)	Area (Sq. Km.)	Area (%)
Agriculture Land	-79.07	-19.06	+111.84	+27.01	+29.40	7.09	+20.71	+5.00	+161.95	+39.10
Built-Up Land	-5.70	-1.38	-1.30	-0.30	-16.35	-4.62	-4.42	-0.43	-22.07	-5.35
Bare Land	-6.83	-1.60	-45.50	-11.00	+19.18	+4.52	+71.99	+17.48	+45.67	+11.00
Vegetation	+91.6	+22.15	-64.19	-15.51	-32.39	-7.22	-81.39	-20.33	-177.97	-43.06
Water Bodies	-0.41	-0.11	-0.72	-0.17	+0.85	-0.20	-7.11	-1.72	-6.98	-1.69

(-ve values indicate an increase and +ve values indicate a decrease)

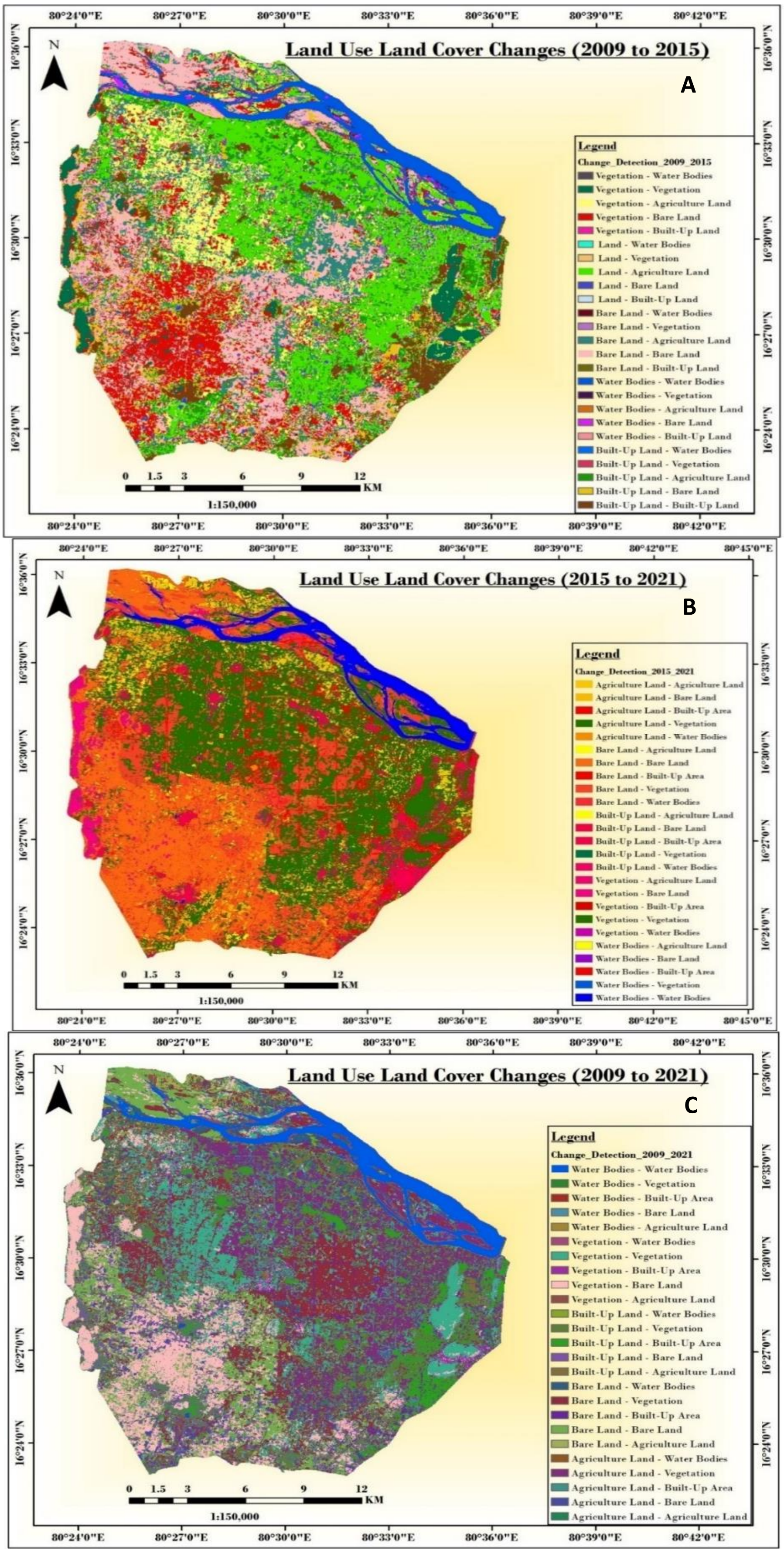


Figure 5: Land use land cover change maps of the study area **(A)** 2009 to 2015, **(B)** 2015 to 2021, **(C)** 2009 to 2021

Table 5: Change matrix of lulc dynamics between 2009 and 2021

	Land Class 2021						
Land Class 2009	LULC Class	Agriculture Land	Bare Land	Built-Up Area	Vegetation	Water Bodies	Grand Total
	Agriculture Land	15.7267	18.0558	19.982	126.537	2.17178	**182.47328**
	Bare Land	3.81221	79.5081	13.0616	55.4709	4.75731	**156.61012**
	Built-Up Land	0.642181	3.30397	13.632	9.09739	0.171112	**26.846653**
	Vegetation	0.548412	10.6266	1.4998	10.1484	1.42404	**24.247252**
	Water Bodies	0.006939	0.347161	0.213266	0.386173	22.2985	**23.252039**
	Grand Total	**20.736442**	**111.841631**	**48.388666**	**201.639863**	**30.822742**	**413.429344**

5. Summary and Conclusions

The rapid growth of urban sprawl can significantly impact urban climate, resources, and the environment. Following 2015, the government of Andhra Pradesh initiated several projects to develop the new capital city, Amaravati, as a planned city, leading to significant changes in LULC. In this context, the study aimed to investigate LULC patterns from 2009 to 2015 and from 2015 to 2021.

This study reveals substantial changes in land use land cover from 2009 to 2021. It demonstrates that agriculture expansion was the primary land use between 2009 and 2015 in Amaravati's study region. From 2009 to 2015, agricultural activity increased sharply, rising from 25.02% in 2009 to 44.08% in 2015. From 2015 to 2021, agricultural activity declined sharply, from 44.08% to 4.98%, representing approximately a 39.10% decrease in the study region. This is due to the rapid development of the state's capital city. In 2015, it was observed that agricultural land was transformed into bare land as a part of land pooling for urban development.

This study examines the dynamics of land use and land cover, including how each class is converted into other classes, as shown in the change matrices presented in tables 4 to 7. Between 2009 and 2021, the percentage of built-up land increased from 5.12% to 11.90%. Another important discovery is that by 2015, the bare land in 2009 had been changed to agricultural land, which turned back into bare land and vegetation (scrub) by the end of 2021. As part of the capital city development, the study region has been transformed from bare land to vegetation cover (open scrub) due to inactive urban development activities. This area remained unused for years, which may result in loss of fertility. This had an impact on local farming methods. Groundwater quality and the exploitation of natural resources will be significantly impacted by the increasing rate of urbanization and the deterioration of agriculture and vegetation.

According to this study, the LULC changes are purely artificial, and it is suggested that the region be used sustainably, promoting urban cultivation practices on a limited scale without compromising its natural character. Creating urban green spaces, roadside plantations, and developing artificial recharge zones, as well as promoting aquaculture and cultivation, are essential for sustainable urban development. More advanced models could be developed to predict future changes and guide mitigation strategies, utilizing advanced tools such as remote sensing, GIS, machine learning, and other techniques to assess LULC changes and their impacts on climate and the environment. This study provides a more precise and actionable assessment of land transformation patterns by integrating advanced classification techniques, high-resolution satellite imagery, and temporal analysis. The insights from this research can be utilized by policymakers, urban planners, and environmental conservationists to inform data-driven decisions for sustainable development in Amaravati and similar urban regions.

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