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Dynamic Landscapes: Unravelling Decadal Changes in Land Use and Land Cover Characteristics

Pureti Siva Nagendram[1,*], Penke Satyanarayana[2] and Panduranga Ravi Teja[2]

[1]*Department of Electronics and Communication Engineering, KLEF, Vaddeswaram, Guntur, Andhra Pradesh, India*
[2]*Department of Internet of Things, KLEF, Vaddeswaram, Guntur, Andhra Pradesh, India*

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Abstract

Accurate land use and land cover (LULC) categorization is vital for effective management of natural resources and monitoring the environment. Technology and machine learning are increasingly used to classify land utilization and landscape coverage. Despite significant advances, land use/cover detection remains difficult. This study uses Landsat 8-OLI satellite data to classify land use /cover. The study focused on area in Guntur district, Andhra Pradesh, India. Landsat satellite data was analysed and classified to quantify temporal changes. This study examined LULC changes in Guntur District from 2018 to 2022. Urbanization and the housing crisis influenced these changes. Based on study area characteristics, five LULC classes were identified. An Accuracy Assessment Classification error matrix and Kappa analysis determined classification precision. For the purpose of comparing changes in Land Use and Land Cover (LULC), both satellite imagery datasets were utilized with a Change Detection approach. Due to Guntur District's housing crisis, vegetation coverage has decreased and built-up and non-incorporated areas have increased, according to this study. Sustainable development and conservation of natural resources in the region require the ability to observe and regulate ecological changes in plant life and land. This study shows how Landsat 8- OLI satellite data and machine learning can accurately classify land use/ cover (LULC). The study highlights that ecological impacts of agriculture and housing crises, emphasizing the need for comprehensive land use and land cover management strategies. Sustainable development and environmental protection require these strategies.

Keywords: land use/land cover, ML algorithm, geo-spatial techniques and accuracy assessment.

1. Introduction

The patterns of how land's used and covered around the world have gone through transformations due, to the rapid growth of human activities and the increasing demand for natural resources. Understanding these changes and their impact on the environment is crucial for resource management and environmental conservation. To achieve this advanced technologies and machine learning methods have become tools for classifying and tracking these land use and cover patterns. This study focuses on examining how machine learning techniques, combined with data from Landsat 8 OLI satellites can be used to classify and detect changes in area of Guntur district, AP, India. However, Guntur district is situated in the state of Andhra Pradesh, India. An area that's well known for its abundant natural resources and fertile lands. Like regions globally Guntur has experienced significant urbanization and industrialization in recent decades. These transformations have had an effect on how the land's used and covered in the area affecting not only the environment but also the ecology and socioeconomic landscape. To establish land use policies, protect the environment and ensure the wellbeing of communities it is crucial to monitor these changes carefully. Managing resources and monitoring changes require the Categorization of LULC. Accurate and, up to date data on land use/cover is crucial for applications like planning, agricultural management, forest conservation and climate change studies.

Traditionally topographic maps and satellite images have been manually interpreted for LU and LC classification. However manual methods have limitations in terms of accuracy and efficiency especially when dealing with study areas or complex land use changes. Consequently there is a growing interest in utilizing technologies like sensing and machine learning algorithms to enhance LULC classification. The advancements in sensing technology have made high resolution satellite data more accessible creating opportunities for monitoring large scale LULC changes with greater accuracy and frequency. The Operational Land Imager (OLI) on Landsat 8 satellite mission by NASA and USGS provides data that's well suited for analysing land cover. With Landsat's resolution it becomes possible to observe gradual and abrupt changes, in both use of land and cover over time. Moreover, machine learning techniques have shown results in automating and improving the process of LULC classification. Computational algorithms have the ability to extract patterns and relationships, from datasets, which can greatly improve the accuracy and effectiveness of classification procedures. By integrating satellite data and machine learning researchers can conduct unbiased analyses of LULC changes. This enables them to make informed decisions regarding resource management and environmental planning. Generating precise LULC maps is crucial but difficult, involving the classification of various categories. Researchers have integrated spectral, statistical, and index-based features to develop LULC maps for urban planning. Utilizing machine learning algorithms has offered a robust approach to city planning.

*E-mail address: sivapureti9316@gmail.com

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The primary way of this study is report is to look at LULC classification using Landsat 8 OLI satellite data in the context of Guntur district, Andhra Pradesh, India. The area focuses on assessing the effects of urbanization and the housing crisis on vegetation cover- and water bodies. The aim is to evaluate changes in LULC within the region, between 2018 and 2022. Additionally, the study will explore the use of ML algorithms to enhance LULC classification accuracy and facilitate change detection.

2. Literature Survey

The significance of detecting changes in usage of region cover using earth observing data, GIS, and advanced technologies in various parts of the world has been examined in a number of research papers. It observed changes in land use and cover. For operational land cover classification, Zhu [1] optimization of training and auxiliary data selection to more accurately categorise land cover and use in Gujarat, India, Thakkar [2] Tasseled Cap Transformation (TCT) was used to perform the hybrid classification. In Ethiopia's Batena Watershed, Ayele [3] carried out multi temporal land use/cover change detection. In order to improve the classification of land use and land cover in Gujarat, India's Arjuni Watershed, Thakkar [4] looked into post classification corrections. In Northern Ethiopia, Ayele [5] carried out Land cover mapping and change detection using time series. To advance land-use and land cover analysis, Moran and Lu [6] Across the globe, the phenomenon of rising surface temperatures due to land use and cover changes and urbanization is prevalent, though the speed of this change is affected by numerous external factors, Partha Pratim Gogoi, V.Vinoj [7] It is apparent that remote sensing plays a critical role in the trend analysis of multi-temporal LULC changes, Anjan Roy , Arun B. Inamdar [8] Urban land cover maps can be employed as a starting point for hierarchical LCZ classification or for determining the extent of human settlements, Chunping Qiu, Lichao Mou [9] Using a single-window algorithm, LST was extracted from Landsat TM/ETM+ data to study variations among different LULC types, JieTan , DeYu [10] The spatiotemporal patterns of LULC changes in Delhi, an interstate planning region that has undergone rapid growth and economic development over the past decades, Mohd Waseem Naikoo,Mohd Rihan [11] Aimed at providing high-resolution satellite data for land cover/use monitoring and tracking climate change and disasters, the Sentinel-2 mission is essential. This focuses on two key areas where evaluating the impact of ESA Sentinel-2 on land cover/use classification, and exploring how well Sentinel-2 data performs in various applications, including forest, urban, and natural hazard monitoring,,DariusPhiri , Matamyo Simwanda , Darius Phiri, Matamyo Simwanda [12] DEM data were utilized to calculate the areas of both changed and unchanged curved land surfaces, which subsequently led to modifications in the land cover change results ,Shuang Hao, Fengshun Zhu.[13] The examination of temporal changes in vegetation indexes was useful for pinpointing seasonal variations in rangelands and can also assist in identifying vegetation phenology, Leonardo Fiusa de Morais, Ana Clara Rodrigues Cavalcante [14] In order to assess the performance of transfer learning architectures for LULC classification, the research utilized two potential models, VGG16 and Wide ResNet-50, which were fine-tuned with the RGB bands of the Euro SAT dataset for classification, Raoof Naushad , Tarunpreet Kaur [15] Penang Island witnessed a significant rise in urbanized and bare lands, coupled with a considerable decrease in green areas, especially those used for agriculture or covered with herbaceous vegetation. The city's forests only showed a slight increase in land area, Gbenga.F,Akomolafe [16] For classifying single-band aerial photographs, a hybrid approach that integrates manual and object-based techniques proves to be very effective, Paria Ettehadi Osgouei, Elif Sertel [17] A framework for self-supervised pre training of deep neural networks has been proposed for the task of land cover classification. This method excels at processing images from multiple sensing modalities, including SAR and multispectral, surpassing traditional approaches such as purely supervised learning, Image Net-based initialization, and other recent self-supervised techniques, Amee K. Thakkar; V. R. Desai [18] the primary focus of this study was to provide LULC change data closely linked to erosion activities. The LULC maps show the centralization and dispersion of various features in near shore regions, placing significant pressure on coastal land use. However, the study faced limitations, particularly with the 1975 satellite image, where atmospheric errors caused disturbances in the analysis. These errors were partially corrected, and each feature was verified using Google Earth Historical , Anindita Nath, Bappaditya Koley [19] Employing a blend of spatial, statistical, and indices-based strategies typically yields stable and reliable results with machine learning algorithms, with artificial neural networks (ANN) being the exception, for both category-level and overall land use/land cover (LULC) classifications in smart city planning, JagannathAryal, Chiranjibi Sitaula [20] proposed integrating optical and polarimetric radar platforms. Together, these studies add significant knowledge about the dynamics of land transformation and its effects on the environment, advancing efforts worldwide for sustainable land management and resource preservation.

3. System Model and Methodology

The system model for accurate Land Use and Land Cover (LULC) categorization based on the provided abstract is outlined as follows

3.1 Data Collection

The field of study is situated in the north eastern part of Andhra Pradesh, India, as shown in Figure 1. It is surrounded by the Bay of Bengal on its southeast, Bapatla District on its south, Palnadu District on its west, NTR District on its northwest, and Krishna District on its north eastern boundary. Covering approximately 2,443 Sqkm (943 sq mi), the area extends between 16.314209 °N latitude and 80.435028°E longitude, with GPS coordinates of 16° 18' 51.1524" N latitude and 80° 26' 6.1008" E longitude. Guntur district, where the study area is located, is primarily an agriculturally dominated region and holds the fourth position in rice production. The region experiences tropical climatic conditions, having a yearly average temperature of 28.5 °C (83.3 °F) and an annual rainfall of about 905 mm (36 in). The influence of the southwest monsoon is apparent throughout the entire area. During the monsoon season (June and July), the region experiences the highest monthly rainfall, with a maximum of 280 mm. In contrast, the 1 mm/monthly minimum rainfall is observed in December. By utilizing sensing and GIS techniques, the study classified the changes in (LULC) in the coastal region. The study area exhibits diverse land utilization patterns, including significant growth in rapid urbanization. Additionally, agricultural land, water bodies, bare land, and forest areas are also found within this region.

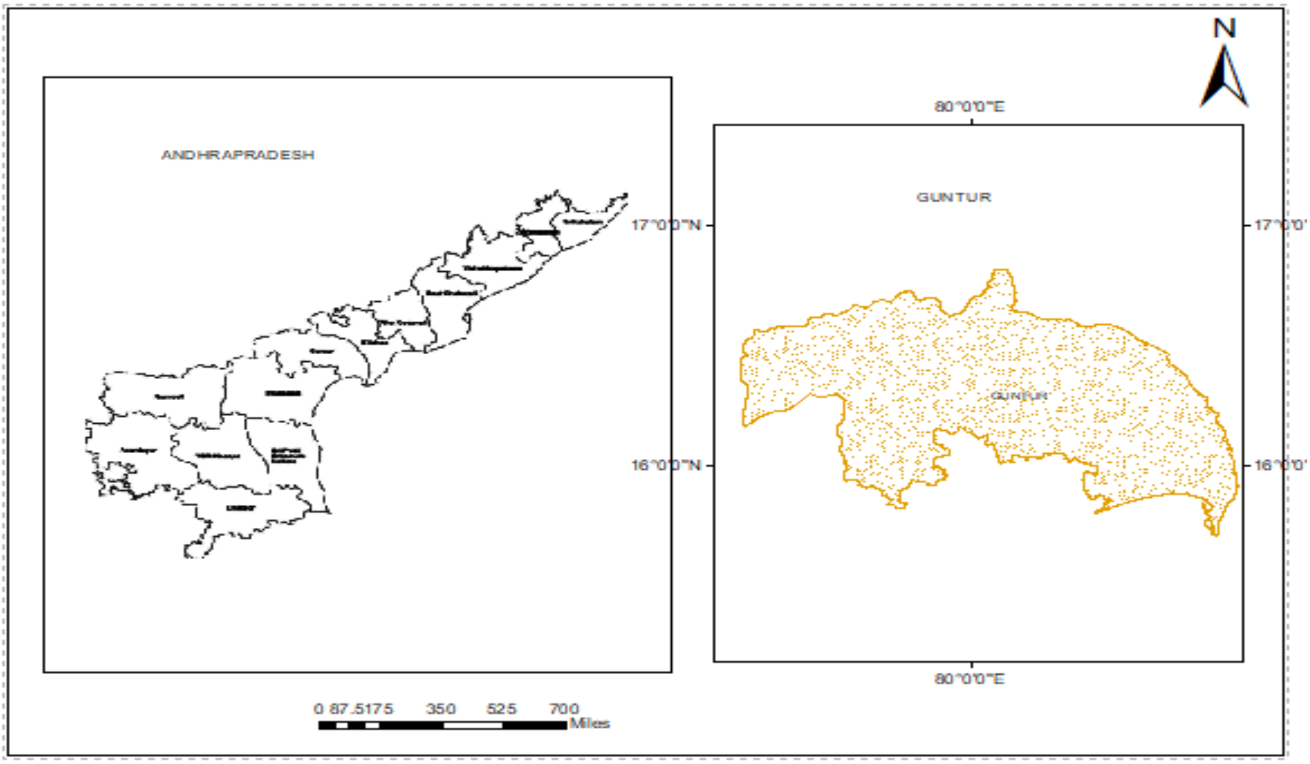

Fig. 1. Study Area

3.2 Land Use and Land Cover Classification

The classification is a crucial process in space observation and GIS (Geographic Information Systems) applications. It involves categorizing and mapping different areas of the land types within a specific geographical area using satellite or aerial imagery. The main objective of LULC classification is to distinguish and assign specific land cover classes, such as forests, agriculture, water bodies, urban areas, barren land, etc., to each pixel or polygon in the image. This classification provides valuable information for various purposes, including natural resource management, environmental monitoring, urban planning, and land-use change analysis. In this approach, satellite imagery were used: an OLI/TIRIS image from 2018 and 2022. Related to the accessibility of high quality satellite imaging, which offers highest level of precision in reference data analysis, OLI/TIRS series images from the years 2018 and 2022 can be used in analysis. In terms of months, the satellite data from 2018 and 2022 were obtained at separate times. After that, the outcome imagery were visually evaluated for mapmaking, however the varying dates of the images had an effect on their accuracy in terms of obtaining the actual ground data for LULC mapping. Since LULC modification is a relatively lengthy process, the study used a 5-year time frame to identify the specific modifications that had occurred. The remote sensing and GIS organisations processed the selected satellite data. There were some geometric, radiometric, and atmosphere correction issues or inaccuracies in the remote sensing data. Due to these drawbacks, radiometric correction and geometric rectification methods were used in the first stage of image pre -processing.

These images were then subset according to their region of interest using software ArcGIS 10.8 after being corrected. ROIs. In the projection process, images for 2018 and 2022 were co-registered. All of the chosen images were projected using the Universal Transverse Mercator (UTM) projection system using zone 44 and the WGS 84 datum. The image for 2018 and 2022 was corrected using the ground control points (GCPs) collected through GPS during the field survey. The primary purpose of this rectification technique is to enhance and improve the quality of images. It permits the minimization of atmospheric errors, which have an impact on the techniques used in digital remote sensing and result in reduced brightness in actual images. The radiometric correction serves in reducing the errors and enhancing brightness quality, which gives images of a specific area or region with more accurate information about it. Radiometric rectification can be used to correct many sources that are impacted by the environment, such as absorption, scattering from darker inclement weather, sensor calibration issues. These sources include aerial photography, satellite data, and even scanned maps. It is possible to extract accurate values from any such source by this method without the interference of any external variables such as changes in the environment. After the pre-processing step we have mosaic and clip the study area region of Guntur district , To generate a training set for LU and LC classification in Arc Map. Import the data into Arc GIS and use the Image Classification toolbar to create training samples by drawing polygons over representative areas for each land cover class. Ensure each sample is correctly labelled. Select a classification method, such as Maximum Likelihood or Random Forest, and use the training samples to guide the classification process through the Image Classification Wizard. After generating the classified image, validate the results with independent ground truth data using accuracy assessment tools to create a confusion matrix and calculate accuracy metrics like overall accuracy and the kappa coefficient. Finally, analyse any misclassifications, refine the training samples as needed, and repeat the classification process to improve accuracy. This method ensures a systematic and accurate approach to land use and land cover classification in Arc Map. Additionally, it helps to improve precision while conducting additional source analysis, ensuring that all outcome are accurate and precise and free from biases caused by outside environmental influences. These data can be used to examine their changes in over period, and pinpoint any areas that seen considerable change by comparing them to the most recent satellite images.

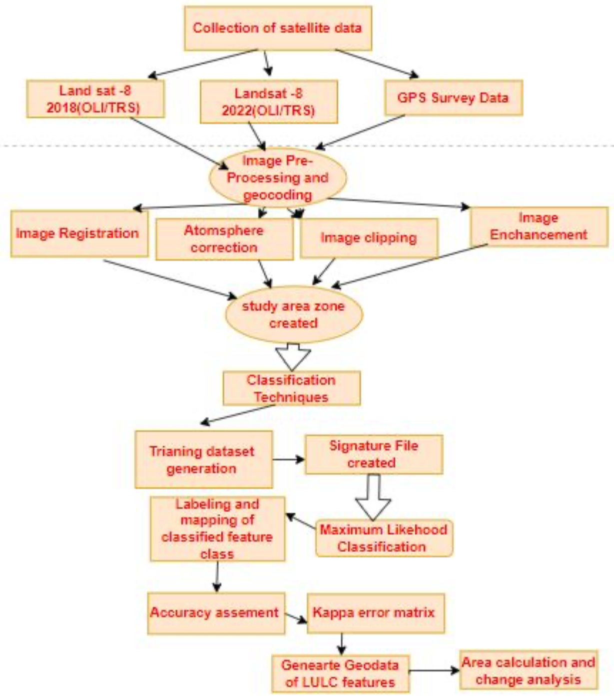

Fig. 2. A schematic flow diagram of methodology

4. Classification Method

The classification process is the most important step in creating a LULC map derived from satellite imagery. Supervised sorting technique is one of the key techniques that is useful for digital image classification systems. Each year image data from 2018 and 2022) was classified for land, cover features separately. The ArcGIS 10.8 programme utilised for the mapping techniques. The current study focused on five different characteristics. (Urban, Land, Forest, vegetation and water areas) which were employed for change studies and generated considerable concentration for region-specific alteration. The study area is mainly formed of agricultural and urban regions. After the pre-processing techniques and noise removal of the image registration. The study area of the zones are to be created along with satellite image. After the training set generations, signature file are to be generated which is a gsg format. The classification is done using the multivariate maximum likelihood classification (MLC) method. The use of these strategies depends on the analyst's specialisation, band selection, data accessibility, landscape complexity, classification algorithm, and knowledge of the topic's area. Because of MLC's stated high degree of accuracy in tropical settings, we chose it over other approaches in this analysis. The fact that MLC is easily incorporated into several popular GIS software applications is another advantage of choosing it. The MLC algorithm operates by allocating pixels to the class with the highest probability and determining which class owns those pixels. Additionally, its data is recognised as having a nearly normal distribution, making it a parametric classifier. We made sure that this classification of the study area was accurate. The following lists the attributes of the characteristics that were chosen: The study area's developed portion is the urbanised area. This comprises buildings, highways, railroads, and businesses. The section of the research area known as agri-cultural land is predominately made up of crops, herbaceous plants, and grasses. The term "bare land" refers to bare soil that has been exposed due to either natural or human activity. The study area includes areas of forests where trees predominate.

4.1 Accuracy Assessment

To ensure the reliability of the organization results, an Accuracy Assessment was conducted using a Classification Error Matrix and KAPPA analysis. The Kappa coefficient (κ) is defined as follows:

$$K=\frac{P_O-P_e}{1-P_e} \quad (1)$$

where p_o is the observed agreement and p_e is the expected agreement by chance.

4.2 Accuracy Analysis in Land Use and Land Cover Classification

The classification method's final step is an accuracy analysis. The classified image is evaluated using statistical methods. Accuracy evaluation from classed images is a step in the integrated LULC feature extraction process. Errors in the classified image are noted from this evaluation, which enhances the accuracy of the information derived. The most important part of any classification process is accuracy assessment. The grouped imagery is compared with another data source that is considered reliable or considered as ground truth data. It can gathered in the field, but this takes time and requires expensive. The interpretation of existing classified imagery, high-resolution photography, or GIS data layers can also yield ground truth data. In order to assess the correctness of your categorised results, a reference dataset is used. Our reference dataset's values must correspond to the schema. Creating a collection of random points from the ground truth data and comparing them to the classified data in a confusion matrix is the most frequent method for determining how accurate a classified map is. Despite the fact that this is a two-step process, you could need to compare the outcomes of other classification techniques or training sites. Alternatively, you might be relying on the same images you used to construct the classification because you lack ground truth data.

4.3 Confusion Matrix

The confusion matrix was finished with the aid of three different classifications: users and producer's accuracy, and overall accuracy assessment based on the omission and commission error rates. Overall accuracy is represented by the following equation:

$$OA=\frac{\text{Total number of correctly classified pixels Diagonal}}{\text{Total number of reference pixels}} X\ 100 \quad (2)$$

4.4 Accuracy

User accuracy is the user's perspective, not the map markers. In short, the accuracy of the user tells us how frequently the class represented on the map will actually be present in reality. This is the reliability that means.

$$UA=\frac{\text{Number of correctly classified pixels in each category}}{\text{Total number of reference pixels in that category (RT)}} X\ 100 \quad (3)$$

where *RT* is the Row Total.

From the viewpoint of the map maker, producer accuracy is map accuracy. This frequently refers to actual ground features that are correctly represented on the map's classification or the likelihood that a certain area's ground.

$$PA=\frac{\text{Number of correctly classified pixels in each class}}{\text{Total number of reference pixels in that class(CT)}} X100 \quad (4)$$

Where *CT* is the Column Total.

4.5 Error classification

Omission Error can happen due to various reasons, such as the limitations of remote sensing technology, misinterpretation of imagery, or human error during the classification process. Minimizing omission errors requires careful image interpretation, validation using ground truth data, and employing advanced classification algorithms to make sure that all pertinent land use and land cover are accurately represented categories in the final map. Each class often has its own omission error computed. This will enable us to assess the classification error and accuracy for each class.

$$\text{Omission Error}=\frac{\text{Number of false negatives}}{\text{Total number of actual instances of the class}}X100.(5)$$

Commission errors are calculated by reviewing the land use and land cover classification. Commission error, also known as false positive, refers to the error that occurs when a particular land cover class is incorrectly included or overrepresented in the classification output.

$$\text{Commission Error}=\frac{\text{Number of false postives}}{\text{Total number of actual instances of the class}} X100(6)$$

Kappa coefficient is a statistical test to assess a classification's correctness yields the kappa coefficient. Kappa evaluates whether the categorization did better than merely randomly assigning values, or if it performed better than random. No classification is superior to random classification than one with a value of 0. If the value is close to 1, then classification is surely superior to random selection.

$$\text{Kappa Coefficient} =\frac{(TSXTCS)-\sum(CTXRT)}{TS^2-\sum(CTXRT)} X100 \quad (7)$$

where *TS* is Total Samples, *TCS* is Total Correctly Classified Sample, *CT* is Column Total, and *RT* is Row Total.

4.3 Change Detection

Change Consideration refers to the process of identifying and analysing the differences or changes that have occurred in a specific area or a set of data over time. In remote sensing and GIS (Geographic Information Systems) applications, Change Detection plays a vital role in various fields, such as environmental monitoring, urban development, agriculture, and disaster management. The process involves comparing two or more datasets acquired at different time points, such as satellite or aerial imagery, to detect and quantify changes in land use, land cover, vegetation, infrastructure, or any other relevant feature. Change Detection can be done using various techniques, including pixel-based methods, object-based methods, and machine learning algorithms. Key steps in Change Detection include data pre-processing, image registration to ensure proper alignment of datasets, and image differencing or comparison to highlight areas of change. The output of Change Detection can be presented as binary change maps, showing areas of change as "changed" or "unchanged," or as thematic change maps, where specific types of changes are categorized and mapped. Environmental and socio-economic impacts are significant due to detected changes in land use and land cover, including rainforest deforestation, urban expansion, and crop farming. Deforestation causes loss of biodiversity, increased CO2 levels, and climate changes. Urban growth converts rural lands into cities, putting pressure on infrastructure and displacing populations. Agricultural expansion degrades soil quality, increases greenhouse gas emissions, and leads to land use conflicts. Change Detection plays a crucial role in decision making processes, as it provides valuable insights into the dynamics of landscapes and urban areas, helps identify potential environmental issues or trends, and aids while creating plans for resource management and sustainable land usage.

5. Simulation Results

5.1 Land Use and Land Cover Status

The quantitative conclusions of the digital LULC classification for the two corresponding years of 2018 and 2022 as shown in table 2. The Guntur district Subdivision spans 1139100 hectares (ha) in total area. Each classification map as shown in figure 2 represents the magnitude of changes in the land use categories and contains five LULC classifications. 2018's spatial distribution patterns of land use indicate that 32 % of the total area was devoted to agriculture, with 21 % going to urban areas. Water and fallow field areas had less coverage overall. From the 2018 year to 2022, agricultural land was covered to a 34% extent. During the time period, both the land area and the surface water areas marginally reduced. The primary topic of this study is how much of the agricultural land is to be covered in Guntur district.

5.2 Accuracy measurement of classification

The produced LULC maps from Landsat imageries were validated by confusing error. Each of the three categories—total accuracy, producer accuracy, and user accuracy—was calculated separately. Table 1 shows a visualisation of the assessment's condensed results. From categorised images from 2022 to 2018, total accuracy scores of 91% and 89% were attained. The kappa coefficient values for the categorised images are 83% and 82%, respectively. In 2022, every land-use class other than vegetation had a producer and user accuracy percentage of more than 80%. The accuracy result indicates that there is a close connection among digital categorization and ground facts (reference points). This was recognised to satisfy the need for change detection analysis and had a logically good overall accuracy.

5.3 User Accuracy (%)

It shows the proportion of pixels that were accurately categorised into each land cover class. From the perspective of a map user. For example, in 2022, the user accuracy for the "Water" class is 100. Table 1 represents the accuracy of the LULC maps for the year 2018 and 2022. It assesses the classification accuracy of different land cover classes based on two measures User Accuracy and Producer Accuracy.

Figure 3 shows the chart representation of LULC map for the academic year 2018 and 2022.

Table 1. Accuracy of Lulc Maps for 2018 And 2022

LULC Name	2022		2018	
	User Accuracy (%)	**Producer Accuracy (%)**	**User Accuracy (%)**	**Producer Accuracy (%)**
Water	100	75	100	83.3
Agriculture	90	96	87.93	94.4
Urban	83.3	83	78.57	91.6
Forest	100	69	100	77.7
Land	87.5	93	93.75	78.9

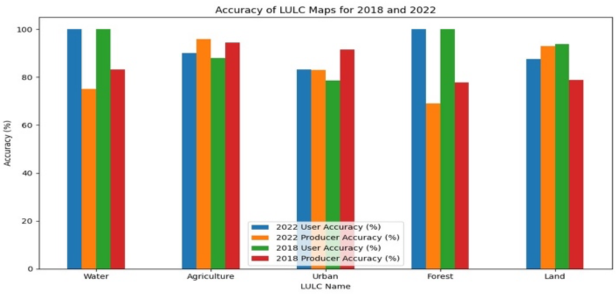

Fig. 3. Accuracy of LULC

5.4 Producer Accuracy (%)

This represents percentage of instances correctly classified pixels for each LC class from the perspective of the map maker or classifier. For instance, in 2018, the producer accuracy for the "Urban" class is 91.6%, indicating that the map maker correctly identified 91.6% of the "Urban" class pixels in the LULC map. Table 2 represents the areas of the LULC maps for the year 2018 and 2022. It shows the spatial distribution of different LU/LC types and how their extent changed over time. Figure 4 shows the chart representation of LULC map for the academic year 2018 and 2022. Figure4 shows the total area in hectares occupied by each land cover class. For example, in 2022, the total area covered by "Agriculture" is 391.2075 hectares. In 2018, "Urban" covers approximately 21.4.

Table 2. Areas of LULC Maps for 2018 and 2022

LULC Name	**2022**		**2018**	
	Area (ha)	**Area (%)**	**Area (ha)**	**Area (%)**
Water	66.63834	6	76.1127	6.0098
Agriculture	391.2075	34	408.9309	32.28
Urban	117.8658	10	271.2593	21.4
Forest	256.65624	23	270.4212	21.35
Land	307.45179	27	239.7422	18.93

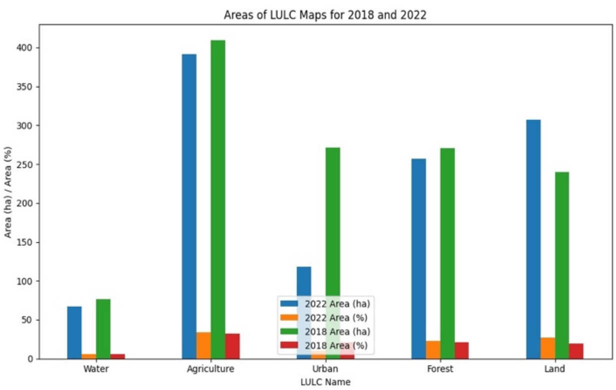

Fig. 4. Area of LULC

5.5 Error Matrix

5.5.1 Omission Error (%)

This refers to the percentage of instances where a particular land cover class was not correctly classified and was omitted (missed) in the LULC map. For instance, in 2022, the "Forest" class has an omission error of 30.7

5.5.2 Commission Error (%)

This represents the percentage of instances where a land cover class was incorrectly included or overrepresented in the LULC map. For example, in 2018, the "Urban" class has a commission error of 21.4%, indicating that 21.4% of pixels classified as "Urban" were not actually part of the urban land cover.

The information in table 1, table 2, and table 3 is crucial for assessing the accuracy and reliability of the LULC classification results. It helps in understanding the spatial distribution of various LC features and the changes that have taken place over time by academics, decision-makers and environmentalists. The accuracy evaluation contributes to the development of categorization techniques and raises the accuracy of data on LU and LC for resource management and decision-making. Table 3 represents the error matrix of the LULC maps for the year 2018 and 2022. It assesses the accuracy of the classification by considering two types of errors: Omission Error and Commission Error. Figure 5 shows the chart represents the error matrix of LULC map for the academic year 2018 and 2022.

Table 3. Error Matrix of LULC Maps For 2018 And 2022

LULC Name	**2022**		**2018**	
	Omission Error (%)	**Commission Error (%)**	**Omission Error (%)**	**Commission Error (%)**
Water	25	0	16.6	0
Agriculture	3.2	9	5.5	12.06
Urban	16.6	6.25	8.3	21.4
Forest	30.7	0	22.2	0
Land	6.6	12.5	21.05	6.25

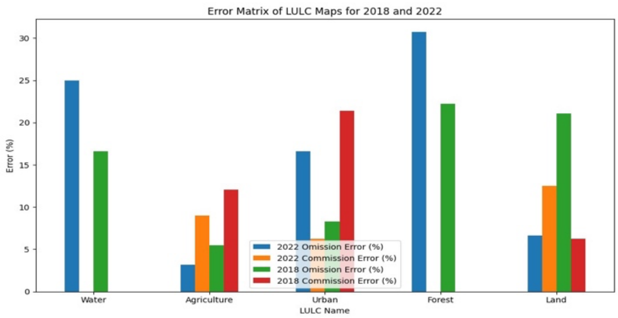

Fig. 5. Error Matrix of LULC

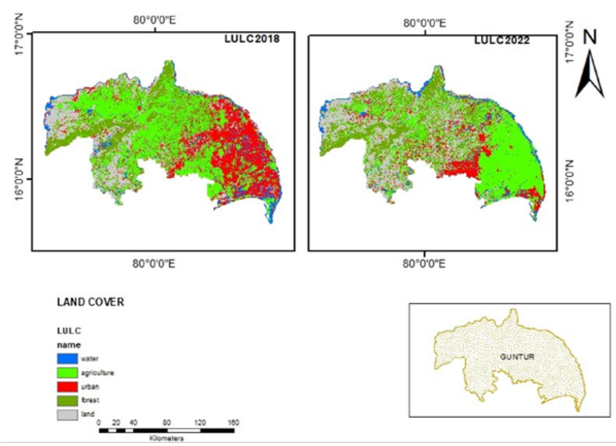

Fig. 6. LULC of Guntur district in 2022, 2018

6. Conclusion

In conclusion, this study highlights the significant decadal changes and evolution in usage of area (LULC) characteristics. Remote sensing and GIS applications remain indispensable for data gathering and monitoring physical agents on the space observations on regular intervals. The analysis using ArcGIS 10.8 software reveals that the entire study area experienced continuous alterations over the examined time period, which is vital for understanding coastal risks and susceptibility resulting from natural and human activities. The primary insert of this research was to assess the accuracy of machine learning classifiers for LULC mapping using satellite observations and identify the best classifier. Landsat 8 (OLI) data for two years were utilized for LULC classification. The Kappa coefficient, an index-based approach, and empirical observations were used to measure accuracy. According to the results, the region under each LULC class varies based on the classifier that was utilised. Agricultural and fallow lands have the most variety, while water bodies show the least variation. This underscores the importance of selecting the most suitable classifier for accurate LULC mapping.

Future research in LULC classification should prioritize advanced machine learning techniques, temporal analysis, and the incorporation of supplementary data sources like LiDAR and socio-economic information. Enhancing accuracy assessment methods and developing automated classification systems leveraging cloud computing are crucial for real-time monitoring. Practical applications span urban planning, environmental protection, agricultural management, disaster risk evaluation, and climate change research. Reliable data will inform policymakers in making land management decisions and resource distribution.

References

[1] Z. Zhu, *et al.*, “Optimizing selection of training and auxiliary data for operational land cover classification for the LCMAP initiative,” *ISPRS J. Photogramm. Remote Sens.,* vol. 122, pp. 206-221, Dec. 2016, doi: 10.1016/j.isprsjprs.2016.11.004.

[2] A. K. Thakkar, V. R. Desai, A. Patel, and M. B. Potdar, “An effective hybrid classification approach using tasseled cap transformation (TCT) for improving classification of land use/land cover (LU/LC) in semi-arid region: A case study of Morva-Hadaf watershed, Gujarat, India,” *Arabian J. Geosci.,* vol. 9, no. 180, Mar. 2016, doi: 10.1007/s12517-015-2267-8.

[3] G. T. Ayele, S. S. Demessie, K. T. Mengistu, S. A. Tilahun, and A. M. Melesse, "Multi-temporal land use/land cover change detection for the Batena Watershed, Rift Valley Lakes Basin, Ethiopia," in *Landsc. Dynam., Soils Hydrolog. Proces. Varied Climat., Springer Geography*, pp. 51–72, Jan. 2016, doi:10.1007/978-3-319-18787-7_4.

[4] A. K. Thakkar, V. R. Desai, A. Patel, and M. B. Potdar, "Post classification corrections in improving the classification of land use/land cover of arid region using RS and GIS: The case of Arjuni Watershed, Gujarat, India," *Egypt. J. Remote Sens. Space Sci.,* vol. 20, no. 1, pp. 79-89, Jun. 2017, doi: 10.1016/j.ejrs.2016.11.006.

[5] G. T. Ayele, A. K. Tebeje, S. S. Demissie, M. A. Belete, M. A. Jemberrie, W. M. Teshome, D. T. Mengistu, and E. Z. Teshale, "Time series land cover mapping and change detection analysis using geographic information system and remote sensing, Northern Ethiopia," *Air Soil Water Res.,* vol. 11, pp. 1-18, Aug. 2018 ,doi: 10.1177/1178622117751603.

[6] E. Moran and D. Lu, "Advancing land-use and land cover analysis by integrating optical and polarimetric radar platforms*," National Science Foundation (NSF), Directorate for Social, Behavioral & Economic Sciences, Division of Behavioral and Cognitive Sciences*, No. 0850615, 2019.

[7] P. P. Gogoi, V. Vinoj, D. Swain, G. Roberts, J. Dash, and S. Tripathy, "Land use and land cover change effect on surface temperature over Eastern India," *Sci. Rep*., vol. 9, Art. no. 8859, Jun. 2019, doi: 10.1038/s41598-019-45213-z.

[8] A. Roy and A. B. Inamdar, "Multi-temporal land use land cover (LULC) change analysis of a dry semi-arid river basin in western India following a robust multi-sensor satellite image calibration strategy," *Heliyon*, vol. 5, no. 4, Apr. 2019, doi: 10.1016/j.heliyon.2019.e01478.

[9] C. Qiu, L. Mou, and M. Schmitt, "Fusing multiseasonal Sentinel-2 imagery for urban land cover classification with multibranch residual convolutional neural networks*," IEEE Geosci. Remote Sens. Lett*., vol. 17, no. 10, Oct. 2020, doi: 10.1109/LGRS.2019.2953497.

[10] J. Tan, D. Yu, Q. Li, X. Tan, and W. Zhou, “Spatial relationship between land-use/land-cover change and land surface temperature in the Dongting Lake area, China,” *Sci Rep*, vol. 10, no. 1, Art. no.9245, Jun. 2020, doi: 10.1038/s41598-020-66168-6.

[11] M. W. Naikoo, M. Rihan, and M. Ishtiaque, "Analysis of land use land cover (LULC) change and built up expansion in the suburb of a metropolitan city: Spatio-temporal analysis of Delhi NCR using Landsat datasets," *J. Urban Manag*., vol. 9, pp. 347-359, Sep. 2020, doi: 10.1016/j.jum.2020.05.004.

[12] D. Phiri, M. Simwanda, S. Salekin, V. R. Nyirenda, Y. Murayama, and M. Ranagalage, "Sentinel-2 data for land cover/use mapping: A review," *Remote Sens.,* vol. 12, Art. no. 2291, Jul. 2021, doi: 10.3390/rs12142291.

[13] S. Hao, F. Zhu, and Y. Cui, "Land use and land cover change detection and spatial distribution on the Tibetan Plateau," *Sci. Rep.,* vol. 11, no. 1, Art. no. 7531, Apr. 2021, doi: 10.1038/s41598-021-87215-w.

[14] L. F. de Morais, A. C. R. Cavalcante, D. do N. Aquino, F. H. M. Nogueira, and M. J. D. Candido, "Spectral responses in rangelands and land cover change by livestock in regions of the Caatinga biome, Brazil," *Sci. Rep.*, vol. 11, no. 1, Art. no. 18261, Sep. 2021, doi:10.1038/s41598-021-97784-5.

[15] R. Naushad, T. Kaur, and E. Ghaderpour, "Deep transfer learning for land use and land cover classification: A comparative study," *Sensors,* vol. 21, no. 23, Art. no. 8083, Dec. 2021, doi: 10.3390/s21238083.

[16] G. F. Akomolafe and R. Rosazlina, "Land use and land cover changes influence the land surface temperature and vegetation in Penang Island, Peninsular Malaysia," *Sci. Rep*., vol. 12, no. 1, Art. no. 21250, Dec. 2022, doi: 10.1038/s41598-022-25560-0.

[17] P. E. Osgouei, E. Sertel, and M. E. Kabadayi, "Integrated usage of historical geospatial data and modern satellite images reveal long term land use/cover changes in Bursa, Turkey, 1858–2020," *Sci. Rep.*, vol. 12, no. 1, Art. no. 9077, Dec. 2022, doi:10.1038/s41598-022-11396-1.

[18] A. Montanaro and D. Valsesia, "Semi-supervised learning for joint SAR and multispectral land cover classification," *IEEE Geosci. Remote Sens. Lett.,* vol. 19, Sep. 2022, doi: 10.1109/LGRS.2022.3195259.

[19] A. Nath, B. Koley, T. Choudhury, S. Saraswati, B. C. Ray, J.-S. Um, and A. Sharma, "Assessing coastal land-use and land-cover change dynamics using geospatial techniques," *Sustainability,* vol. 15, no. 9, Art. no. 7398, Apr. 2023, doi: 10.3390/su15097398.

[20] J. Aryal, C. Sitaula, A. C., and L. Frery, "Land use and land cover (LULC) performance modelling using machine learning algorithms: A case study of the city of Melbourne, Australia," *Sci. Rep.,* vol. 13, no. 1, Art. no. 13510, Aug. 2023, doi:10.1038/s41598-023-40564-0.