Land use and Land cover classification for temporal analysis on Ganjam District Region, Odisha using Remote Sensing and Google Earth Engine

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Abstract

Land use/land cover change (LULC) affects natural ecosystems and the environment, which can lead to changes in land resources, biodiversity, ecological functions, and environmental components. This is why LULC Change Analysis plays an important role in planning and using current and future natural resources for the sustainable development of any country. This paper performs LULC classification and analysis over a study region in Ganjam District, Odisha, India. Satellite data was extracted from Landsat 7 and 8 satellites that provide spectral and multi-temporal images. For the LULC classification, 5 LULC classes were considered such as water bodies, vegetation, urban areas, barren Land, and cropland. A machine learning-based approach was applied using Google Earth Engine (GEE) to compare different supervised classifiers such as Support Vector Machine (SVM), Classification and Regression Trees (CART), and Random Forest over the periods between 2010 and 2020. In this study, SVM gave the best results with 92 percent Overall Accuracy(OA) and 0.90 Kappa Value. Also, the change analysis showed that Urban areas increased by 112 percent, cropland by 9 percent, and barren land decreased by 68 percent between 2010 and 2020.

Keywords: *Remote Sensing, LULC, GEE, Landsat, SVM, CART,*

Problem Statement

The state of Odisha in India has experienced rapid land use and land cover (LULC) changes over the last decade due to different anthropogenic and natural factors. Understanding these changes is very important for land management and sustainable development. To address these challenges, this research aims to utilize remote sensing data from Landsat 7 and 8 satellites and the powerful analysis capabilities of Google Earth Engine to conduct LULC classification and change analysis in the Ganjam district region. The study seeks to develop an accurate and efficient approach to analyze the change in the area between 2010 and 2020 using supervised machine learning algorithms such as SVM, Random Forest, and CART.

Introduction

Land Use and Land Cover(LULC) are terms that encompass all the Earth's physical features such as forests, barren lands, water bodies, etc. as well as all the regions that humans utilize for their functional needs such as cities, croplands, and water resources. Classifying and mapping the land use and land cover regions on a map is called LULC classification. Today, extensive research is being done in the field of LULC classification due to its association with crucial social as well as ecological factors. LULC classification maps not only aid in environmental management and sustainable development, but they also serve as a crucial source of information for efficient decision-making and other facets of urban management. Land use and land cover information is pivotal for successful land administration and planning. It helps us distinguish appropriate areas for diverse activities such as farming, building cities, and setting up industries. LULC classification maps greatly aid in monitoring natural resources and identifying distinctive regions such as sandy areas, desolate lands, and marshy swamps. Knowing these regions is vital to ensure wildlife, protect water, and keep a variety of flora and fauna alive. Climate change analysis requires precise and up-to-date LULC information to understand the impacts of land use changes on the environment. For instance, analyzing and studying the changes in urban areas can indicate when rapid urbanization has occurred. As urbanization is linked with increased surface heat levels and air pollution, it can cause serious altercation to the climate and the environment around the area. Studying the patterns in which change in LULC occurs can help in diminishing the chance of disasters as it can imply approximately where natural catastrophes are likely to happen, like floods, avalanches, rapidly spreading fires, etc. based on past data. This is why LULC classification is so critical and why these maps must be kept up-to-date.

Traditionally, Land Cover and Land Use maps were created by experts manually visiting the landmarks, collecting the ground observations, and classifying them based on field surveys and visual interpretations. This was an inefficient method that was very time and energy-taxing. Due to these inefficiencies and the availability of huge amounts of high-quality data, new methods such as classification based on sensory and spatial satellite data are used today. In this study, Landsat 7 and 8 satellites are used for LULC classification and change analysis for the years between 2010 and 2020. Landsat satellites are operated by the United States Geological Survey (USGS) and NASA. These satellites give an in-depth analysis of different LULC regions by storing and collecting multispectral, temporal, and sensory data for the Earth's surface. Landsat 7 and Landsat 8 are the latest satellites in the program, known for their ability to capture data across various spectral bands. All the bands store different types of sensory and visual information that experts use to solve various problems. Landsat satellites have a spatial resolution of 30 meters and a revisit time of 16 days.

Google Earth Engine (GEE) is employed as the base platform on which the whole study is conducted. Some parts of the study which involve extensive programming are done on Google Collab using Python API GEE. Google Earth Engine is known for its satellite data and geospatial analysis capabilities. It has a huge collection of satellite data stored in its online database, which is easy to work with. Also, it operates on a cloud-based infrastructure which eliminates the need for high-end machines and computing power. This completely changes the game and makes the whole process efficient and cost-effective. This is the reason GEE is used for this study.

The objectives for this research are:-

- LULC classification map for the study area.
- Comparative Study of different machine learning models.
- Calculating area change between 2010 and 2020.

The study area for this research is a region in Ganjam District located in Odisha, India. Figure 1 shows a basic map of the district. It has rich flora and fauna and facilitates a variety of biodiversity and diverse landforms. Also, it is considered one of the major districts in Odisha. Its location is 84.7° to 85.12° east longitude and 19.4° to 20.17° north latitude. It has an area of 8070 sq. km. Summer in the Ganjam district is hot and sticky which begins in March and lasts till May. Temperatures amid this time are around 30°C to 40°C. Winters are milder, enduring from December to February, with temperatures extending from 15°C to 25°C. The Ganjam District incorporates a rainy climate, characterized by particular wet and dry seasons. The rainy season which starts in June lasts till September. This period gets most of the district's yearly precipitation, around 1444 mms. Ganjam District incorporates a diverse topography incorporating coastal fields, stream valleys, uneven territories, etc. It is broadly partitioned into two parts: the coastal plain range within the east and slope and table lands within the west. Apart from this, multiple natural challenges require the government's consideration and immediate action. Soil disintegration, Deforestation, and urbanization are a few issues that are affecting this region. This is where LULC classification can offer assistance in monitoring environmental changes and providing sustainable solutions.

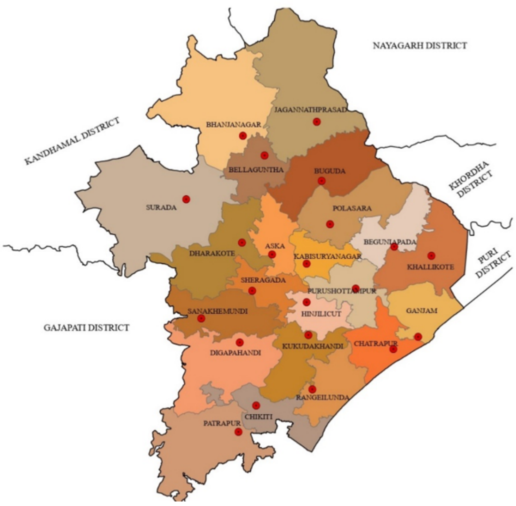

Figure 1: Map of Ganjam District

Literature Survey

The purpose of this literature review is to provide an overview of the different methods and techniques researchers use to identify, classify and analyze changes in LULC classification using remote sensing and GIS. The various methods highlighted in these papers are Maximum Likelihood Classification, multilayer perceptron, SVM, RF, and CART.

A study by Abdulkadir Giado[1] explained how one can use remote sensing and GIS to understand land use and land cover and monitor various spatial and temporal changes in them. It discussed different techniques researchers use to categorize changes and decide how the land is used. These techniques included MLA, MLC, CD, and MCA.

A study conducted by Khazaei [2] looked at how Google Earth Engine (GEE) can be used to map land use and land cover (LULC) on a large scale. It also reviewed other previous studies that used remote sensing techniques. The problems with using pixels-based methods for classification are addressed here and the advantages of using objects-based classification instead of pixel-based methods are demonstrated.

S. Kiran's [3] study focused on the LULC classification in the Ramagundam coal mining area using remote sensing and GIS methods. This study looked at previous research on detecting changes in land use and land cover and emphasized how important it is to monitor these changes, especially in areas that are developing quickly or affected by the environment. It concluded that machine learning algorithms like CART and SVM perform best in LULC classification.

In a study conducted by S. Swetanisha [4], machine learning algorithms were used to classify LULC in the Kendrapara District, Odisha. The models used were Support Vector Machine (SVM), XGBoost, and an Ensemble Model that combined SVM and XGBoost. It used Landsat 7/8 imagery from 1999 and 2020 to see if there were any changes in agricultural land and cities. They were interested specifically in detecting urban growth.

A study conducted by Lei Ma [5] reviewed more than 200 research publications for analyzing the usage of deep learning algorithms in remote sensing problems. The researchers conducted various experiments while paying attention to the hyperparameters, the resolution, the types of areas they studied, and how accurate their classifications were. Moreover, the study looked at different ways DL can be used in remote sensing, like combining images and object-based image analysis (OBAI).

A study by C. G. Karishma [6] used geospatial techniques to analyze land use and cover changes in the Lower Bhavani Basin, Tamil Nadu, India. Land-use changes from 2014 to 2019 were studied. MLC, SVM, RF, and ANN were used in this research where SVM and RF were found to achieve the highest accuracy.

A study by Jane Ferah Gondwe [7] analyzed urban land use and cover changes in Blantyre City using remote sensing technology. It aimed to analyze remote sensing data to identify changes in land use categories such as residential areas, commercial areas, industrial zones, vegetation cover, and open spaces in Blantyre City. Image classification, change detection, and spatial analysis techniques were used to analyze land use and cover changes. The results informed urban planning, land management, and policy-making by providing them with key insights into efficient urban development and sustainable solution generation.

In a study conducted by Kotapati Narayana Loukika [8], machine learning algorithms, such as Support Vector Machine (SVM), Random Forest (RF), and Classification and Regression Trees (CART), were employed for land use and land cover (LULC) classification. Performance metrics were evaluated using accuracy ratings obtained from Google Earth Engine. The study utilized

Sentinel-2 and Landsat 8 satellite imagery with 10 and 30-meter resolutions to classify LULC categories for the years 2016, 2018, and 2020, including 'water', 'forest', and 'barren land'. The RF classifier exhibited higher accuracy rates, achieving 94.85% for Landsat-8 and 95.8% for Sentinel-2, outperforming SVM and CART. The RF classifier showed high accuracy in LULC classification.

A study by Wang et al. (2019) [9] used Landsat time series data and RF classification to analyze urban land use and cover change. It concludes that RF is effective at processing complex datasets with high-dimensional features and is suitable for analyzing large-scale time-series data.

Yue Zhu's [10] research used multitemporal remote sensing data to enhance the LULC classification accuracy. The convolutional LSTM model was used to learn spatiotemporal properties from remotely sensed photos by combining convolutional and LSTM layers.

According to [6], we can conclude that supervised methods have achieved better accuracy than unsupervised methods for LULC classification. Hence, for this research, state-of-the-art classifiers such as Support Vector Machines (SVM), Random Forest (RF), and Classification and Regression Trees (CART) are used as the machine learning algorithms for land use and land cover classification. These classifiers were chosen for their proven effectiveness and suitability for our specific research goals. SVM is a powerful algorithm that can process complex datasets with high-dimensional features, Random Forest can withstand noise and is very flexible, and CART is a tree-like structured classification and regression algorithm that is easy to understand and highly interpretable. These algorithms are compared and utilized to classify land use and land cover in this study accurately. These methods have shown their strength in past studies, giving a strong basis for our approach and helping our research be successful.

Methodology

Existing System Issue:

Traditional Methods:

Though some may consider Land use and land cover (LULC) classification as a novel practice, it has been used by field surveyors for centuries for collecting land cover information and developing various topographic and ecological maps. The field surveyors visited the landmarks manually and did all the research and data collection based on visual interpretation. They also identified and mapped different land cover types based on appearance and characteristics.

Simple LULC Classifications:

Nowadays, there are a wide variety of classification and mapping algorithms that utilize machine learning and remote sensing data still, there are only very few that give precise LULC change analysis over a long period and provide effective visualizations for the classification. This is a vast field of study, that is still not much explored and utilized.

Proposed System

Flowchart

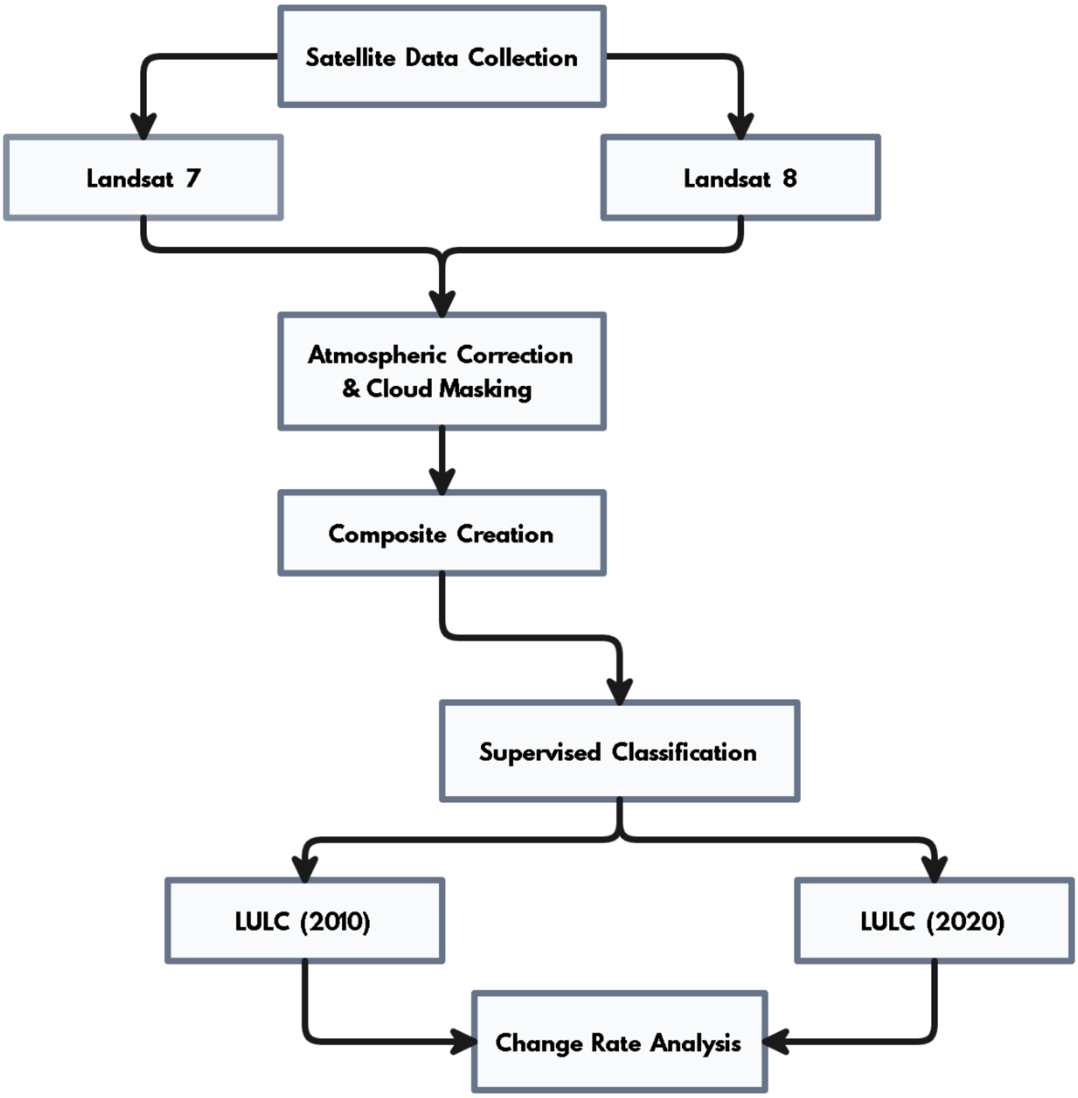

Figure 2: Working of LULC classification

Satellite Data Acquisition

Firstly, the area of interest(AOI) was established by precisely delineating the boundaries of the selected sub-region within the Ganjam District, Odisha. This approach ensures a targeted analysis, facilitating accurate and context-specific LULC classification results. After that, Remote Sensing spectral and temporal data was extracted from LANDSAT 7 ETM+ and LANDSAT 8 OLI/TIRS satellites which are provided by the GEE platform. GEE has access to vast resources and archives, in particular Earth Engine Data Catalogue which is leveraged to import the image collections for creating training data for the LULC classification model. Landsat satellites have multiple bands which store different kinds of sensory information. The most used bands are Bands 4,3,2 as they are RGB bands that are required for visualization.

Table 1: LANDSAT 7 Bands Information

Band Number	Band Name	Wavelength Range (micrometers)	Spatial Resolution (meters)
Band 1	Coastal/Aerosol	0.45 - 0.52	30
Band 2	Blue	0.52 - 0.60	30
Band 3	Green	0.63 - 0.69	30
Band 4	Red	0.77 - 0.90	30
Band 5	Near Infrared	1.55 - 1.75	30
Band 6	Shortwave	2.08 - 2.35	30
Band 7	Mid-Infrared	2.09 - 2.35	30
Band 8	Panchromatic	0.52 - 0.90	15

Table 1 summarizes the spectral bands and spatial resolutions of the Landsat 7 Enhanced Thematic Mapper Plus (ETM+) sensor. Landsat 7's ETM+ sensor has eight spectral bands, of which one is a panchromatic band with a higher spatial resolution than the rest of the bands. A band's wavelengths are given in micrometers, and its spatial resolutions are listed in meters.

These bands are beneficial for an assortment of uses, containing:

- Land cover classification: The various spectral signs of diverse land cover types can be used to classify land cover.
- Vegetation scanning: The spectral feedback of plants changes as it evolves and ripens, so the ETM+ bands can be used to monitor plants.
- Water quality assessment: The ETM+ bands can be used to determine water characteristics by weighing the assimilation of light by water and deferred sediments.

Table 2: LANDSAT 8 Bands Information

Band Number	Band Name	Wavelength Range (micrometers)	Spatial Resolution (meters)
Band 1	Coastal/Aerosol	0.43 - 0.45	30
Band 2	Blue	0.45 - 0.51	30
Band 3	Green	0.53 - 0.59	30
Band 4	Red	0.64 - 0.67	30
Band 5	Near Infrared (NIR)	0.85 - 0.88	30
Band 6	Shortwave Infrared 1	1.57 - 1.65	30
Band 7	Shortwave Infrared 2	2.11 - 2.29	30
Band 8	Panchromatic	0.50 - 0.68	15
Band 9	Cirrus	1.36 - 1.38	30
Band 10	Thermal Infrared 1	10.60 - 11.19	100
Band 11	Thermal Infrared 2	11.50 - 12.51	100

Table 2 summarizes the spectral bands and spatial resolutions of the Landsat 8 Operational Land Imager (OLI) sensor. The OLI sensor has 11 spectral bands, containing a panchromatic band accompanying a bigger spatial resolution than the additional bands. The wavelengths of the bands are recorded in micrometers, and the spatial resolutions are filed in meters.

The table supplies a summary of the spectral bands and dimensional determinations of the sensor, that may be used to select the appropriate bands for a certain use.

Here are a few supplementary analyses about the bands:

- Band 1 (Coastal/Aerosol): This band is good for detecting seaside features and aerosols in the air.
- Band 9 (Cirrus): This band is beneficial for detecting cirrus clouds.
- Band 10 (Thermal Infrared 1): This band is favorable for weighing surface climates.
- Band 11 (Thermal Infrared 2): This band is again beneficial for weighing surface climates.

Pre-processing

Cloud Masking:

A cloud masking algorithm was created to find and remove the cloudy pixels from the spectral data. It is a preprocessing technique that is applied to the raster image collection extracted from the Landsat satellites. Clouds act as a hindrance to the satellite's view of the Earth's surface and thus reduce the accuracy of the overall LULC classification process. The cloud masking algorithm works by analyzing the spectral properties of the satellite imagery. Typically, clouds appear brighter in the visible and near-infrared bands and exhibit higher reflectance values.

Using GEE API, the QA band of Landsat satellites was analyzed for the cloud pixels which contain specific bits representing cloud and shadow information, and then bitwise operations were applied for the cloud reduction.

Adding extra bands:

Additional bands such as the Normalized Difference Vegetation Index (NDVI), Normalized Difference Water Index (NDWI), and Bare Soil Index (BSI) were added to the raw satellite data to capture certain land cover characteristics which are not usually visible using original bands and also to increase the overall accuracy.

NDVI = (NIR - Red) / (NIR + Red) **(1)**

NDBI = (SWIR - NIR) / (SWIR + NIR) **(2)**

BSI = ((SWIR + Red) - (NIR + Blue)) / ((SWIR + Red) + (NIR + Blue)) **(3)**

Composite creation:

After cloud masking and adding extra bands, the raw satellite data image collection from Landsat 8 and 7 was converted to a composite image to mitigate any influence of seasonal variations and atmospheric conditions on LULC classification. The median of the temporal data is taken to create a composite image.

Training Data

For creating the training data required by the ML model, geometric points for different LULC classes were taken. They were separated into five classes: Water, vegetation, urban, cropland, and barren. For each class, approximately 90-100 points are extracted manually followed by the overlay of the geometric points on the raster image of the AOI which was obtained using Landsat satellite. This created a labeled training dataset with each point having bands and indices as its features and the LULC class as the output label.

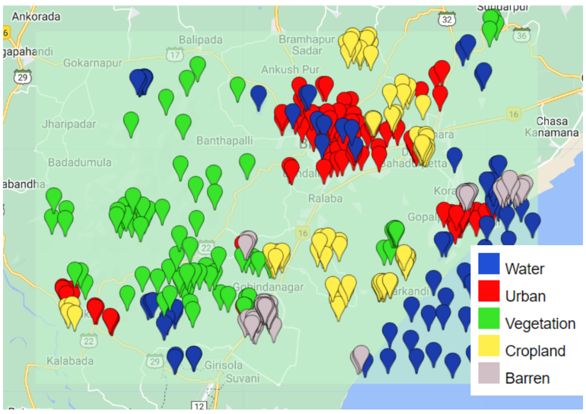

Figure 3: Labelled Training Data

Figure 3 shows a map of the study area in G, accompanying the identified training data points for the LULC classification. The training data is prepared on Google Earth Engine (GEE), and it consists of polygons that are divided into various land cover classes, in the way that:

- Vegetation: This class refers to unrefined, evergreen, and temperate forests.
- Cropland: This class refers to different croplands used for farming.
- Urban: This class refers to cities and towns.
- Water: This class refers to different water bodies as well as water resources like rivers. ponds and waterways.
- Barren: This class refers to the fields that are unable to support plant growth.

Supervised Classification

For Supervised Classification, the training data created in GEE was imported into Collab using the ee.FeatureCollection function provided by GEE API. Classification using Machine Learning involves multiple steps- splitting training and test data, tuning hyperparameters for different classifiers, and finally testing the classifiers. For LULC classification, the training data was separated into training and testing datasets, where 70% of the data was used for training and 30% for testing. For the feature selection, the training set was overlaid over the Landsat raster map of the Ganjam District region so that it captures all the geospatial information related to it. Also, the visual parameters and band information were specified. For supervised classification, stat-of-the-art classifiers were selected-SVM, CART, and Random Forest which were later compared for best accuracy and then implemented using GEE's inbuilt machine learning functions.

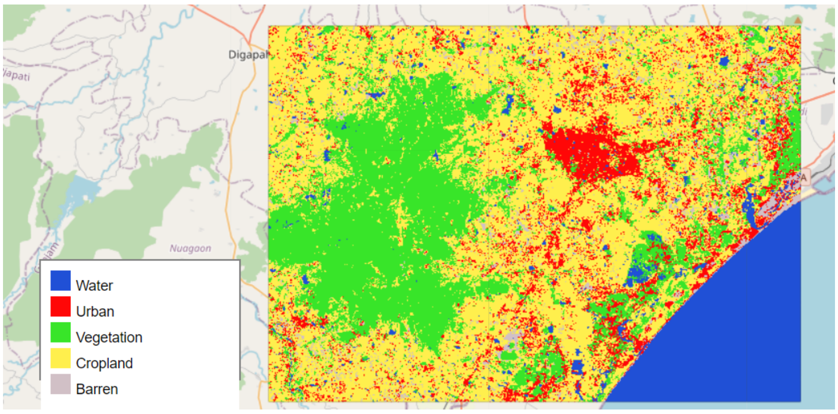

Figure 4: Model performing LULC Classification using the Training dataset

Figure 4 showcases the final result produced by supervised LULC classification. The machine learning model used here is Support Vector Machine (SVM) which classifies various LULC classes based on visual parameters set by the user into different color schemes-blue for the Water class, red for the Urban class, green for the vegetation class, yellow for the cropland class, and grey for the barren class. The model learns to associate the spectral signs of various LULC classes accompanying their equivalent labels.

Classification Algorithms

Random Forest:

Random Forest is an ensemble learning method that works by combining multiple decision trees to provide better classification results with higher accuracy. It can handle a lot of diverse data such as numeric, and categorical which is why it can be considered a great classifier for LULC classification. In this study, Random Forest was employed using ee.Classifier.smileRandomForest() function provided by Python API GEE. The hyperparameters it uses are:- the number of decision trees, variablesPerSplit, minLeafPopulation, bagFraction, maxNodes, and seed. After the train-test split of the training data, feature selection was conducted to select relevant features and spectral bands which were given to the Random Forest algorithm as input. The main input given to the algorithm were the geometric points extracted from the training data, band information, and label information for various LULC classes.

rf_classifier = ee.Classifier.smileRandomForest(5).train(training,label,bands) **(4)**

rf_classified = input.select(bands).classify(rf_classifier) **(5)**

SVM:

Support Vector Machine (SVM) is an algorithm that's exceptionally well-known for classification problems. In SVM, the algorithm tries to find a hyperplane within the vector space that can partition different classes viably. It works by maximizing the gap between the support vectors of distinctive. It is exceptionally great at dealing with high-dimensional data and can perform classification on complex and expansive volumes of information. In this study, SVM was employed using ee.Classifier.libsvm() function provided by Python API GEE. The hyperparameters it uses are:- decisionProcedure, svmType, kernelType, shrinking, degree, gamma, coef0, cost, nu, terminationEpsilon, lossEpsilon, and oneClass. After the train-test split of the training data, feature selection was conducted to select relevant features and spectral bands which were given to the SVM algorithm as input. The main input given to the algorithm were the geometric points extracted from the training data, band information, and label information for various LULC classes.

```
svm_classifier = ee.Classifier.libsvm( decisionProcedure='voting',      (6)
   kernelType='LINEAR',
   shrinking=True,
   cost=4,
    ).train(training,label,bands)
svm_classified = input.select(bands).classify(svm_classifier)           (7)
```

CART:

CART which stands for Classification and Regression Tree is a supervised learning method used for both classification and regression problems. It incorporates a splitting process in which the information is split optimally in recursion based on particular criteria such as information gain or Gini impurity. It stops when a stop criterion is met such as the maximum no. of trees. It is very well known since it is highly interpretable and can discover non-linear connections between the data. In this study, CART was employed using ee.Classifier.smileCart() function provided by Python API GEE. The hyperparameters it uses are:- maxNodes, and minLeafPopulation. After the train-test split of the training data, feature selection was conducted to select relevant features and spectral bands which were given to the CART algorithm as input. The main input given to the algorithm were the geometric points extracted from the training data, band information, and label information for various LULC classes.

cart_classifier = ee.Classifier.smileCart(maxNodes=50, (8)

minLeafPopulation=9).train(training,label,bands)

cart_classified = input.select(bands).classify(cart_classifier) (9)

Result and Accuracy Assessment

For assessing the ML models, the Overall Accuracy, Kappa Value, and error matrix were considered. Based on the error matrix the Overall Accuracy, User Accuracy, Producer's Accuracy, and Kappa value were calculated. Table 3 shows that for Landsat 8, SVM had the best results with Overall Accuracy of 92% and a Kappa value of 0.90. Random Forest had the second-best result with an Overall Accuracy of 90% and a Kappa value of 0.87. And CART had the worst results with Overall Accuracy of 87% and a Kappa value of 0.84.

Table 3: ML model comparison between SVM, Random Forest, and CART

Model	Overall Accuracy	Kappa Value
SVM	92%	0.90
Random Forest	90%	0.87
CART	87%	0.84

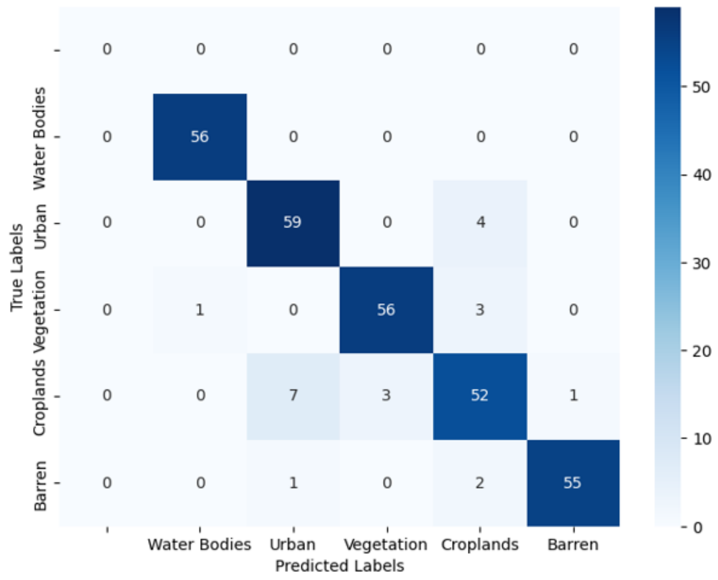

Figure 5: Confusion Matrix for our Labelled Training Data built on GEE

Figure 5 shows a confusion matrix for the classification results produced by the SVM model for 2020. Different LULC classes-Barren, Cropland, Vegetation, Urban, and Water Bodies are compared and analyzed for getting the actual validation for the model's accuracy. A confusion matrix is a table that shows the anticipated and real classes for a set of data. The rows of the matrix show the anticipated classes, and the columns show the real classes. The values in the containers of the matrix depict the number of representations that were precisely classified.

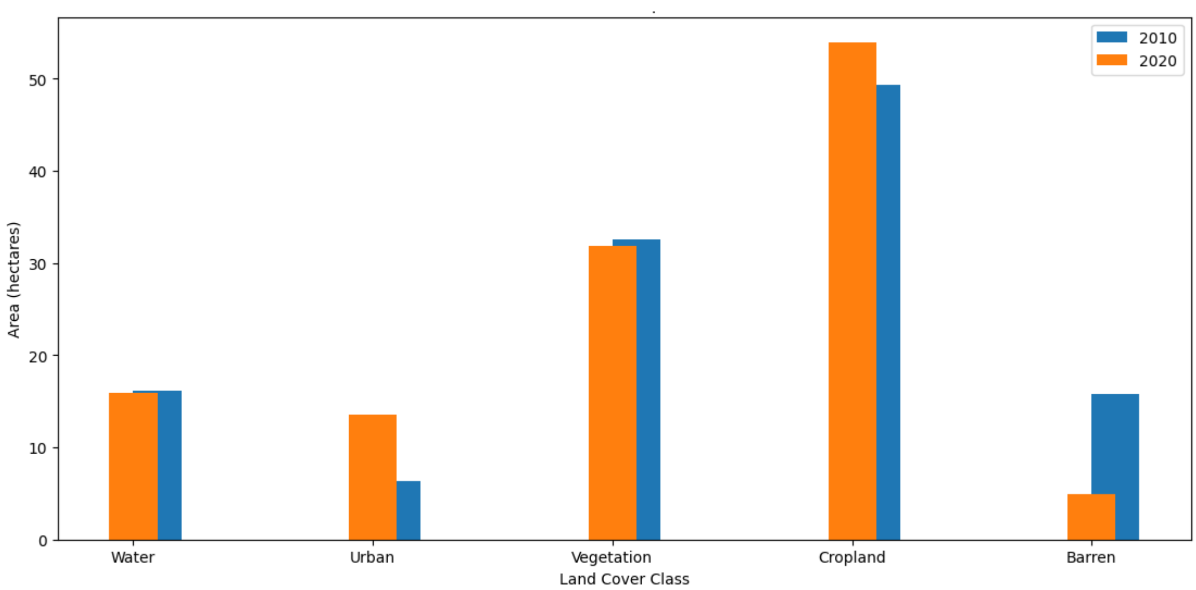

Figure 6: LULC Class Distribution Comparison between 2010 and 2020

Figure 6 shows a bar graph equating the distribution of land use and land cover (LULC) classes in 2010 and 2020. The bar graph shows for most classes, few changes happened in the LULC class distribution between 2010 and 2020. The major change was in urban and barren lands where the portion of urban lands increased massively and the barren lands decreased immensely in area.

Table 4: Area change analysis table for the period between 2010-2020

Class	Area_2010(sq. Meters)	Area_2020(sq. Meters)	Area change(Percentage)
Water Bodies	161615.91	158727.07	-1.78%
Urban	63856.35	135739.85	112.57%
Vegetation	326095.89	319141.71	-2.13%
Cropland	493435.14	539986.15	9.43%
Barren	158081.85	49490.35	-68.69%

Figure 6 showcases that the majority of the land cover change occurred in the Urban and Barren LULC classes. Table 4 gives the complete Area change analysis:-

1. The Water Bodies class covered a total of 161615.91 sq. Meters of land area in 2010 and 158727.07 sq. Meters of land area in 2020. The final results show that the water bodies decreased in size by 1.78%.
2. The Urban class covered a total of 63856.35 sq. Meters of land area in 2010 and 135739.85 sq. Meters of land area in 2020. The final results show that the urban area increased in size by 112.57%.
3. The Vegetation class covered a total of 326095.89 sq. Meters of land area in 2010 and 319141.71 sq. Meters of land area in 2020. The final results show that the vegetation decreased in size by 2.13%.
4. The Cropland class covered a total of 493435.14 sq. Meters of land area in 2010 and 539986.15 sq. Meters of land area in 2020. The final results show that the cropland increased in size by 9.43%.
5. The Barren class covered a total of 158081.85 sq. Meters of land area in 2010 and 49490.35 sq. Meters of land area in 2020. The final results show that the barren land decreased in size by 68.69%.

Discussion

The study demonstrates that between the years 2010 and 2020, rapid urbanization took place. This can be seen by the 112.57% increase in the land cover area for urban areas from 63856.35 sq. meters in 2010 to 135739.85 sq. meters in 2020. This might be due to the government's development of infrastructure such as transportation networks, roads, bridges, and public utilities. Also, The rapid industrialization in Odisha created numerous job opportunities, particularly in sectors such as manufacturing, mining, construction, information technology, and services. The government policies to promote urban development also attracted a lot of investments and businesses.

The Vegetation and water bodies did not change much- vegetation area decreased by 2.13% and the water bodies decreased by 1.78%. On the other hand, the cropland increased by 9.43% in area, which can be seen as a side product of rapid urbanization. Surprisingly what changed the most apart from the urban area was the barren area which reduced by 68.69% from 158081.85 sq meters in 2010 to 49490.35 sq. meters in 2020. Since 2010, the government has taken lots of measures to reduce soil degradation and erosion which leads to the creation of barren lands. Also, efforts were made for land reclamation and rehabilitation which ultimately reduced barren areas. These might be some of the reasons why the change in land cover between 2010 and 2020 took place.

Conclusion

In this paper, LULC classification was performed on the Ganjam District region in Odisha, India for the years between 2010 and 2020 to analyze the change that might have happened in the geographic landscapes and regions which the LULC occupied. Raster image data collected from Landsat 7 and 8 were used as the training data. The classification was implemented using state-of-the-art ML classifiers SVM, CART, and Random Forest which were compared and experimented to find the best classifier. The experiment indicated that SVM gave the best accuracy with 92% Overall Accuracy and 0.90 Kappa Value. The change analysis results showcased that there was a huge increase in the urban area by 112.57% and a decrease in the barren area by 68.69%.

Odisha is a state rich in biodiversity and various landforms. But, the mapping of different LULC classes has yet to be done extensively for this region, especially after 2010. That is why this research is significant as it provides vital geospatial information about LULC classes for the Ganjam district in Odisha with a focus on the temporal range between the years 2010 and 2020. This information can help policymakers, environmentalists, and decision-makers to manage natural resources by getting a deeper understanding of the land cover of the study area. This is the main strength of this paper. However, future research for this region is required by using long-term period change analysis and experimenting with Deep Learning(DL) classifiers.

Future Work

Though this research paper gives an in-depth analysis of LULC classification for the Ganjam District region, further research can be done in many fields. Firstly, conducting LULC classification for a longer duration of time can provide a more in-depth and comprehensive understanding of long-term trends and patterns in LULC changes. Also, experimenting and implementing Deep Learning models such as Radial basis function Neural Networks (RBFNN), Convolutional Neural Networks (CNNs), and Recurrent Neural Networks (RNNs) may lead to improvement in accuracy and efficiency. The integration of ancillary data, such as climate data and topographic variables with satellite data can also be put into further research. This can further enhance the accuracy of LULC classification and also give a better understanding of the different drivers and impacts of land cover changes. By incorporating these additional geospatial data, researchers can gain insights into the underlying processes driving LULC classification and also improve the Overall Accuracy of the classifier. By exploring these future research directions, advancement can be made in LULC dynamics and support sustainable land management practices in the Ganjam District and similar regions.

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