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Comprehensive Land Use and Land Cover Classification in Chhatrapati Sambhajinagar City, Maharashtra, India, Using Satellite Imagery and Machine Learning Techniques

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Abstract: In This research presents an extensive analysis of land use and land cover (LULC) classification in Chhatrapati Sambhajinagar City, a rapidly expanding urban center in Maharashtra, India, highly susceptible to climate change. Using remote sensing and GIS techniques, the research evaluates the impact of LULC on ecosystem service values (ESV) over a nine- year period (2013-2021). Satellite-based data were utilized to quantify LULC changes, encompassing Green Area, Buildup Area, Road Area, Water Bodies, and Barren Land. The research employs five distinct classification methods and investigates the effectiveness of pre-processing techniques in improving classification accuracy during selected years (2013, 2016, 2019, and 2021). The performance of Mahalanobis Distance, Maximum Likelihood, Parallelepiped, and Support Vector Machine methods is assessed under both preprocessed and non-preprocessed conditions, using overall accuracy and Kappa accuracy as evaluation metrics. The results reveal consistent enhancements in overall accuracy, with Mahalanobis Distance, Maximum Likelihood, and Support Vector Machine methods demonstrating percentage improvements ranging from 0.43% to 5.08% after preprocessing. Particularly noteworthy are the substantial percentage increases in Parallelepiped Classification, ranging from 23.74% to 53.34%, highlighting the transformative impact of preprocessing on its accuracy. These findings emphasize the necessity for customized preprocessing strategies to refine the precision of LULC classification models, offering valuable contributions to the realms of remote sensing and geospatial analysis. Moreover, the insights gleaned from this research provide crucial guidance for urban growth management and climate resilience strategies in rapidly developing urban areas, making it a valuable resource for sustainable urban planning.

Keywords: Land use, Land cover, Landsat 8, Maximum Likelihood, Mahalanobis Distance, Support Vector Machine, Parallelepiped Classification, Chhatrapati Sambhajinagar City, Urban environment.

I. INTRODUCTION

Chhatrapati Sambhajinagar, nestled in the heart of Maharashtra, India, is a city of historical grandeur and cultural significance. Its name pays homage to the Mughal emperor Aurangzeb, whose reign left an indelible mark on its heritage [1]. At a distance of approximately 335 kilometers east of Mumbai, the state capital, Chhatrapati Sambhajinagar stands as a hub of historical and architectural marvels. The city's crowning jewels are the UNESCO World Heritage Sites of the Ajanta and Ellora Caves, adorned with ancient rock-cut Buddhist, Hindu, and Jain temples that narrate tales of India's rich spiritual legacy [2]. Culturally, Chhatrapati Sambhajinagar is a vibrant mosaic, where Marathi, Urdu, and Hyderabad traditions converge harmoniously. This blend of cultures permeates every aspect of life in the city, from its eclectic cuisine that tantalizes the taste buds to its spirited celebrations of festivals that captivate the soul [3]. Chhatrapati Sambhajinagar's economic tapestry weaves together a diverse range of activities. Industries such as manufacturing, agriculture, tourism, and education thrive here. Notably, the city is home to the ambitious Chhatrapati Sambhajinagar Industrial City (AURIC), a sprawling Greenfield industrial smart city poised to drive economic growth and innovation [4]. As of the last update in September 2021, Chhatrapati Sambhajinagar boasted a population of over 1.1 million inhabitants [5]. However, it is crucial to consider that demographic figures may have evolved since then, and researchers are advised to rely on the latest available data for accuracy. To unravel the complexities of land cover in Chhatrapati Sambhajinagar City, we employ three distinct classification techniques.

Firstly, the Maximum Likelihood method is employed, a widely used statistical approach for classifying pixels based on spectral characteristics. Secondly, the Mahalanobis Distance Classification and Parallelepiped Classification, which considers the covariance between different bands of satellite imagery, is applied to enhance classification accuracy. Lastly, the Support Vector Machine (SVM) method, known for its robustness in handling high-dimensional data, is deployed as a powerful tool in our analysis [6]. Our research meticulously evaluates the accuracy of these classification techniques, shedding light on their respective strengths and weaknesses when applied to the dynamic urban environment of Chhatrapati Sambhajinagar City. By comparing the results across the Four chosen years, we gain valuable insights into the dynamics of land use changes within the city.

II. LITERATURE REVIEW

In an urban transition scenario, land use change combined with a lack of UGS stewardship resultsin small, fragmented, and degraded UGS [7]. One of the biggest challenges in this situation is the lack of capacity to plan and implement change [8]. Due to the unavailability of data or recordsof the current situation of UGS [9]. This lack of a complete dataset coupled with rapidadministrative boundary expansion and unauthorized land conversion in the urban transition process makes the monitoring and management of UGS a more complex process.

The local authorities fail to understand the associated trade-off of land allocation and its implications on the overall urban environment of a city. The local authorities refer to the cadastral maps for planning, monitoring, and management of UGS, however, these maps fail to represent the detailed landscape character, the diverse set of functions performed by UGS, their distribution, and other associated attributes.

This lack of base data in understanding the complex and dynamiclandscapes prevalent in cities becomes one of the major hindrances in the decision-making process.

Thus, the need for more detailed maps (spatial data) with spatial heterogeneity of the quantity and quality of services provisioned to guide a more integrated understanding of UGS arises. The spatial dataset augmented with detailed landscape layers facilitates the effective communication and evaluation of the service supply or the demand side of UGS [10].

For whichgeographic information system (GIS) is very effective and widely accepted as an “automated system for the capture, storage, retrieval, analysis, and display of spatial data” [11]. GIS allowsoverlaying different information in an integrated manner that is perceptive and communicable todifferent stakeholders [12]. Hence, GIS effectively integrates, represents, and communicates datato guide the planning process of UGS. These remotely- sensed data are widely used for Land UseLand Cover Change (LUCC) studies. The coarse spatial scale (30 m resolution) identifies greenspaces consistently across larger geographical units generated during the classification process Of imagery, in the form of arbitrary polygons with distinctive land cover, however, the data maynot be meaningful to planners in terms of units recognizable on the ground [13].

The classification of remotely-sensed data is based on the reflectance of ground cover, which is converted into polygons with distinct land cover, however, the unit size and the classes of greenspaces considered are broad and lack functional classification and ownership details (e.g., privateor public green spaces), which are necessary for managed landscapes. Thus, the need to generate spatial data that considers other attributes of human-dominated landscapes. In addition,quantitative green space cover arises to allow more sophisticated approaches for analyzing greenspaces for urban planning purposes [14]. Hence, the maps generated by analyzing the remote-sensing data, are referred to as thematic maps [15].

Which combine “spatial and on-spatial data” were explored as an important tool for dataset preparation in this study. Few studies showcase the increasing use of GIS in planning, such as in Vietnam, a dataset of urban trees and green space of two cities was prepared by mapping in GIS [16].

Some more authors have used it to map urban green infrastructure and understating land cover change [17].In India, as mapping of protected green spaces (national parks and forest), urbanization and changing land use land cover trends, green space quality, and quantity study at the neighborhood scale are evident in recent publications [18]. However spatial data with finer details are mostly unavailable.

Though this is vital for planning and decision-making, at presentspatial and digitized data for UGS is not available for most Indian cities, thus adversely affectingthe planning process. A recent study by Angularity and Narayanan also highlighted the need forgreen space mapping to support land allocations during master plan preparation for emerging urban centers [19]. Thus, to protect, manage and effectively plan the threatened and stressed UGSin an integrated manner, it is important to record what is prevalent in the city. With this context,the study endeavors to develop a mapping methodology to create a thematic map of public UGSfor Chhatrapati Sambhajinagar city as a case.

III. MATERIALS AND METHODS

A. Research Area

Chhatrapati Sambhajinagar city was taken as the research area (Figure 1), which is also a representative example of a typical mid-level emerging urban center in Maharashtra, India [20]. The city ranks as the 43 biggest urban agglomeration in country and 5th biggest city in the state of Maharashtra. It is the administrative headquarters of Chhatrapati Sambhajinagar district and is the largest city in the Marathwada region [21]. Located on a hilly upland terrain in the Deccan Traps, Chhatrapati Sambhajinagar is the fifth-most populous urban area in Maharashtra after Mumbai, Pune, Nagpur and Nashik with a population of 1,175,116. The city is known as a major production center of cotton textile and artistic silk fabrics.

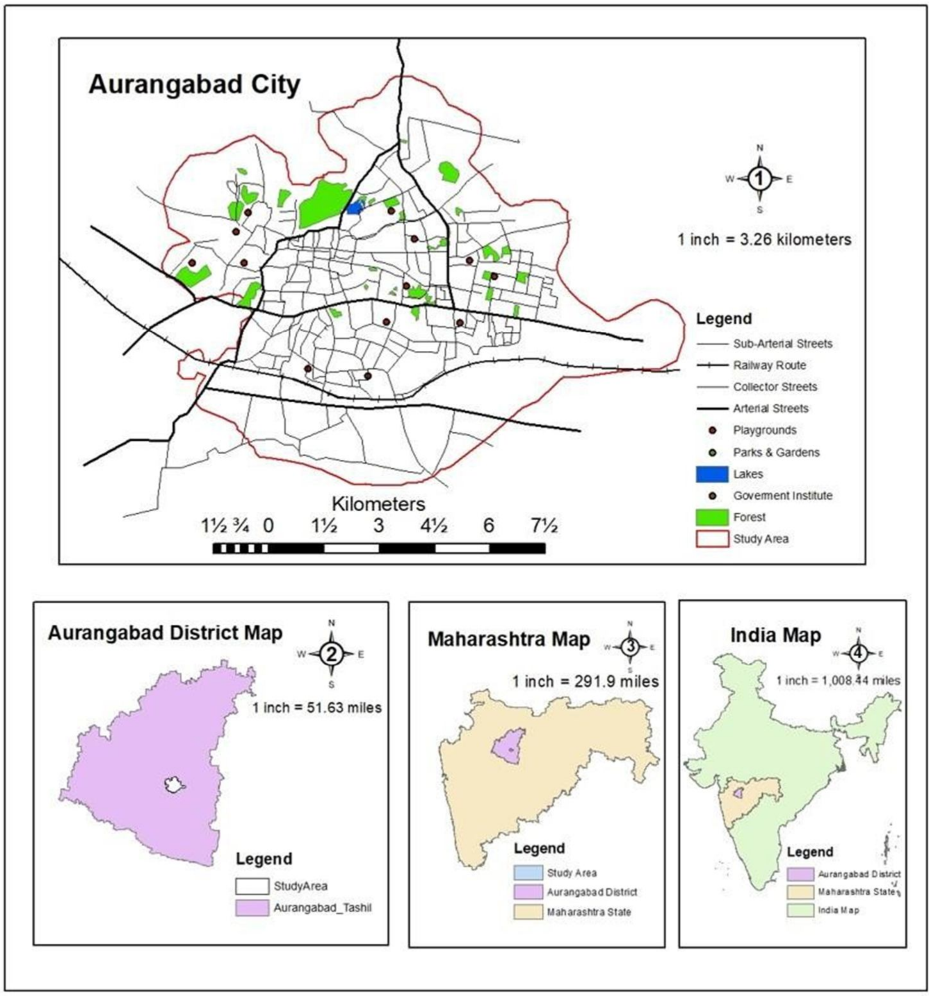


Figure 1. Geographic Location of Study Area Location Chhatrapati Sambhajinagar City, Maharashtra, India.

B. Data Source

In this research, 2013 is chosen as the earliest year for the data analysis based on the low image resolution and data availability of satellite images and the quality of the existing reference dataset. Data are available through the year 2021. The geometrically corrected data of Landsat Level 1 products were downloaded from the United States Geographical Survey (USGS) [22]. The research followed 9-year intervals to visualize the difference in LULC dynamics. Spatial data were acquired at a resolution of 30 m from the Landsat-8 Operational Land Imager (OLI) images were used for the year for the 2013, 2016, 2019, and 2021. More details of the acquired data are shown in Table 1. The acquired data period was selected for the post-monsoon period (October to December), which mostly has vegetation green to semi-evergreen [23]. And free from cloud cover [24]. After downloading data from the USGS source was pre-processed by extracting the research area, radiometric and atmospheric correction using ENVI.

Table 1. Landsat Data Used for the Research.

Landsat	Path/Row	Spatial Resolution	Acquired Year
Landsat 8 OLI/TIRS	141/41	30m	2013, 2016, 2019 , 2021

C. *Pre-Processing*

To avoid data error or tampering and to establish a direct link between data and biophysical processes, satellite images have to be pre-processed. Each Landsat image is an L1 product, and geometric corrections were performed during data pre-processing. This research used atmospheric and radiometric correction procedures in ENVI 5.5 for removing atmospheric noises and surface reflectance caused by the earth's rotation [25]. All of the images were processed for radiometric calibration (digital number (DN) to Top of Atmosphere (TOA)) and atmospheric corrections (25-26). The atmospheric correction eliminated the effect of atmospheric absorption and scattering, which gives true surface reflectance data [27]. As the band composition is very important for LULC classification and every Landsat sensor has a different band, those bands were carefully composited into one layer. The framework of this research is shown in Figure 2.

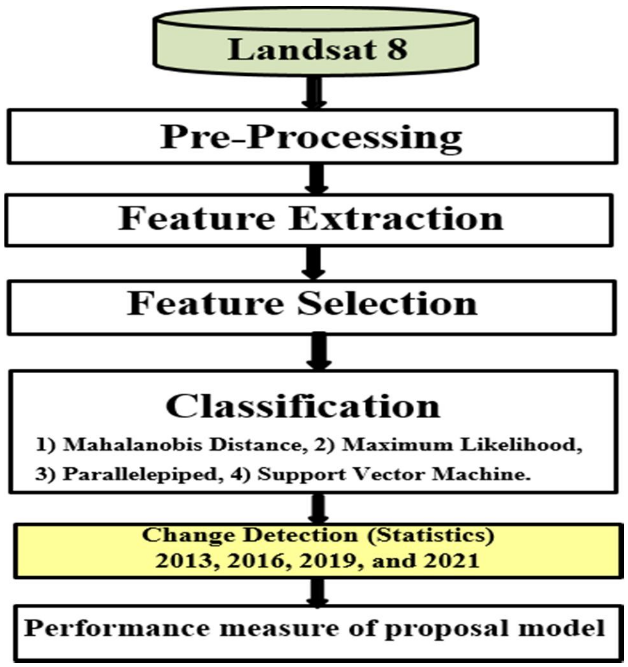


Figure 2. Flow of Research Study

D. *Feature Extraction*

The feature extraction process begins by Regions of Interest (ROI) are raster samples used in classification statistics extraction. ENVI performs real-time orthorectification on ROI layers, displaying projected coordinates on existing RPC images acquiring and Pre- Processing high-resolution satellite imagery covering Chhatrapati Sambhajinagar. Image enhancement techniques are applied to improve visual quality and highlight vegetation-related features. Relevant spectral bands and indices sensitive to vegetation cover are selected for analysis. Ground truth data is collected through field surveys to delineate various land cover classes, including urban green spaces. Using this labelled data, supervised classification methods like Maximum Likelihood Classification (MLC), Mahalanobis Distance Classification (MDC), Support Vector Machine (SVM), and Parallelepiped Classification are employed. These methods utilize spectral signatures to classify pixels and distinguish urban green spaces from other land cover types. Accuracy assessment techniques are applied to validate the classified maps, refining them as needed. The final maps depict the extent and distribution of urban green spaces in Chhatrapati Sambhajinagar, aiding in informed urban planning and environmental management decisions.

E. Feature Selection

Principal Component Analysis (PCA) and Minimum Noise Fraction (MNF) are tools used in ENVI to reduce dimensionality in multispectral or Multispectral data. PCA transforms original variables into principal components, while MNF maximizes signal- to-noise ratio in Multispectral data. Choosing the appropriate technique depends on experimentation and data characteristics.

F. Classification

In this research, the LULC classification uses a supervised classification method. In supervised classification, Maximum Likelihood Classification (MLC), Mahalnobis Distance Classification (MDC), Support Vector Machine (SVM), and Parallelepiped Classification is the most widely used parametric algorithm, and it gives better classification results for quantitative analysis. At first, a number of signatures of each land class were generated for data training. These signatures were grouped manually into predefined land classes using simple random sampling, high-resolution Google Earth, and subject-matter expertise and familiarity with the research area. For remote sensing image classification, the quality and quantity of selection of training samples are largely related to the accuracy of overall classification. In order to get a better classification result, more sample of each land cover type were selected for training data [28]. Then supervised classification was carried out of all Landsat image using Maximum Likelihood Classification (MLC), Mahalnobis Distance Classification (MDC), Support Vector Machine (SVM) and Parallelepiped Classification. Based on the degree of similarity and properties of pixels, Maximum Likelihood Classification (MLC), Mahalnobis Distance Classification (MDC), Support Vector Machine (SVM) , and Parallelepiped Classification is categorized into one of the land class groups. In this research, five land cover types were selected based on the land use types and intensity of land use changes. Table 2 shows the major land cover types and their description of their characteristics in the research area. The descriptions of land cover types in the table below describe the nature and characteristics of land classes in the research area.

Table 2. Major Land Use and Land Cover types.

Land Cover Types	Description
Green Area	A land dominated by trees, including natural woodlands and community plantations
Buildup Area	Residential, commercial, industrial, roads, and construction site
Road Area	All road network is administered by various government authorities build-up
Water Bodies	All types of water bodies such as rivers, ponds, and Lakes
Barren Land	Areas of silt and sand with very little or no vegetation, such as the shores of rivers

G. Statistics and Accuracy Assessment

The final and most important step during the land cover type classification in the remote sensing data process is accuracy assessment or validation [29]. Accuracy assessment is an important activity due to the possibility of inaccuracy in the Landsat data. It compares the produced data by the user with the real ground truth data. The accuracy of classified land cover classes was measured using an error matrix [30], user accuracy, producer's accuracy, overall accuracy and Kappa coefficient to verify the precision and error of the images by comparing them to actual ground truth points [31]. The accuracy assessment of land cover data was carried out using the generally accepted stratified random sampling method. Google Earth provides high-resolution satellite photos at no cost, which are critical references for validating the LULC classification [32]. In order to understand the accuracy of classified land classes, samples of actual ground truth data of each class were taken randomly and compared to classified land classes. The number of samples of each class sample depended on the area of the land class. First of all, an accuracy assessment point was created in classified data in GIS which was exported to Google Earth (Google Earth Pro version 7.3). Each random point was verified by comparing it with the ground truth for accuracy assessment. For this research , Google Earth images from December 2013 and 2021 were used as the reference for classified land classes of 2013 and 2021, respectively, and a 1:63,360 scale topographic map as a reference for classified land classes of 2013 and 2021. An error matrix was generated using reference points.

$$\text{Producer's Accuracy} = \frac{C_{xx}}{\sum r} \times 100\%$$

Where, C_{xx} is the element at position x^{th} row and x^{th} column and $\sum r$ is row sums.

$$\text{User's Accuracy} = \frac{C_{yy}}{\sum c} \times 100\%$$

Where, $\sum c$is column sums 0

$$\text{Overall Accuracy} = \frac{\sum_{x=1}^{r} c_{xx}}{N} \times 100\%$$

Where, N and A is the total number of pixels and classes respectively.

$$k = \frac{\sum_{i=1}^{r}(X_{ii} - \sum ci \sum ri)}{N^2 - \sum_{i=1}^{r}(\sum ci \sum ri)}$$

Where, r= number of rows and columns in the error matrix, Xii = number of observations in row i and column i, $\sum ci$ = marginal total of column i, $\sum ri$= marginal total of row i, N = total number of observations and k= Kappa Coefficient Accuracy.

The overall accuracy of the classified image is determined by comparing how each satellite image cell is classified to the definite land cover conditions acquired from the actual land cover. The likelihood of a categorized pixel matching the land cover type of its corresponding real-world place is measured by the user's accuracy [33]. Producer accuracy is a measure of how well real-world land cover types can be classified. The kappa coefficient is a frequently used method for agreement with classified and actual land cover and is calculated using equation 1 shown below for each land cover classification. The kappa coefficient value ranges from-1 to +1; the higher the value, the greater, the agreement.

$$\text{Kappa Coefficient} = \frac{\sum_{i=1}^{m} x_{ii} - \sum_{i=1}^{m} x_{ii}(A_i C_i)}{n^2 - \sum_{i=1}^{m} x_{ii}(A_i C_i)}$$

where n is the total number of stratified random samples taken, xii gives the number of samples in actual class i, Ai is the total number of actual ground truth samples associated with class i, Ci represents the total number of the classified sample belonging to class i, m is numbers of rows and columns in the error matrix.

Table 3. Result without Pre-processing Overall Accuracy.

	Without Pre-processing – Overall Accuracy			
	2013	2016	2019	2021
Mahalanobis Distance Classification	88.66%	86.45%	83.57%	82.67%
Maximum Likelihood Classification	90.49%	87.79%	87.19%	87.51%
Parallelepiped Classification	43.94%	27.53%	67.11%	69.89%
Support Vector Machine Classification	88.15%	89.66%	86.30%	93.25%

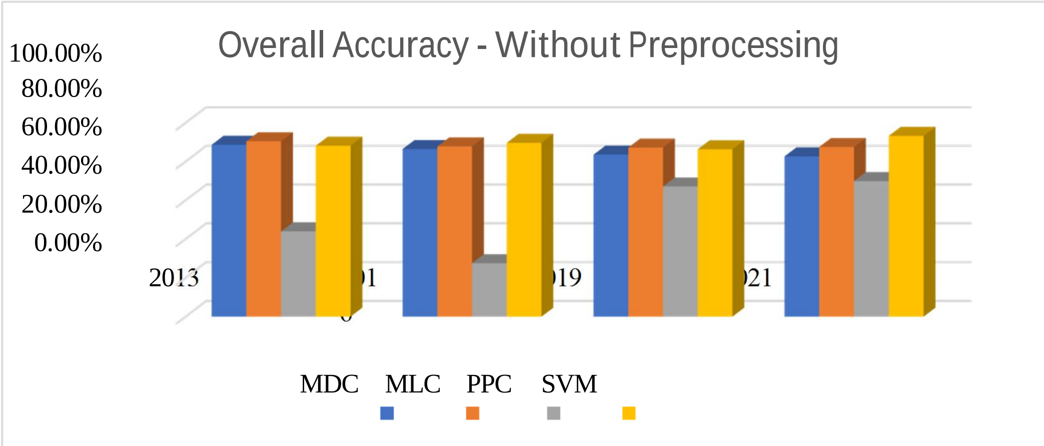
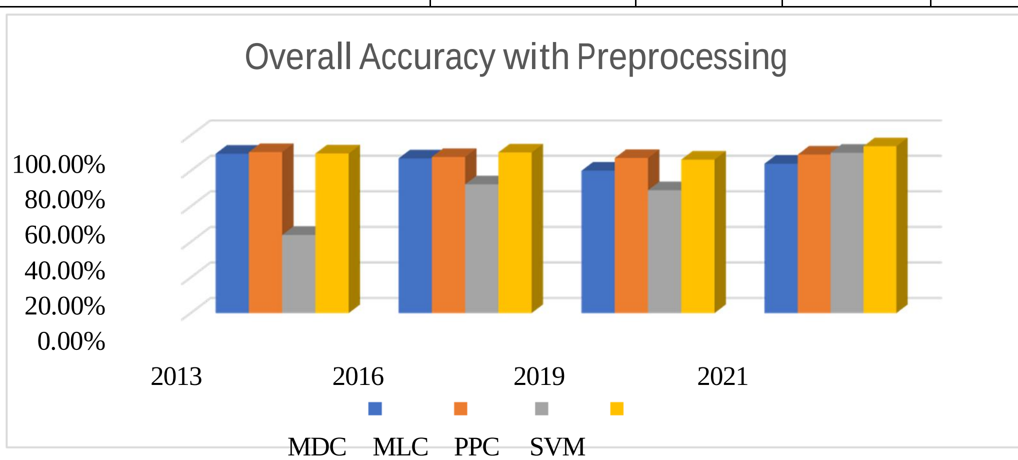


Table.4 Result with Pre-processing Overall Accuracy

	With Pre-processing – Overall Accuracy			
	2013	2016	2019	2021
Mahalanobis Distance Classification	89.62%	86.98%	80.09%	84%
Maximum Likelihood Classification	90.55%	87.82%	87.22%	89.13%
Parallelepiped Classification	43.91%	72.38%	69.12%	90.18%
Support Vector Machine Classification	89.77%	90.33%	86.34%	93.84%



The table 3rd and 4th provides a comparative analysis of land cover classification techniques the comparison of land use and land cover (LULC) classification results before and after pre-processing with Overall Accuracy demonstrates consistent improvements in accuracy. Maximum Likelihood and Support Vector Machine methods consistently achieve high accuracy percentages in both scenarios, with Maximum Likelihood ranging from 87.19% to 90.55% and Support Vector Machine from 86.30% to 93.84%. Parallelepiped Classification shows substantial improvement post-pre-processing, with accuracy increasing from 27.53% (2016) to 90.18% (2021). Mahalanobis Distance Classification exhibits varying performance, with accuracy ranging from 82.67% to 88.66% without pre- processing and improving to 80.09% to 89.62% after pre-processing. These findings underscore the method and year-specific impacts of pre-processing on LULC classification accuracy, highlighting the importance of tailoring pre- processing techniques to the characteristics of the data and the chosen classification method.

Table 5. Result without Pre-Processing Kappa Accuracy.

	Without Processing – Kappa Accuracy			
	2013	2016	2019	2021
Mahalanobis Distance Classification	83.54%	82.07%	75.80%	74.15%
Maximum Likelihood Classification	86.18%	83.86%	81.58%	81.16%
Parallelepiped Classification	25.90%	2.16%	57.79%	53.02%
Support Vector Machine Classification	82.32%	86.31%	79.95%	89.30%

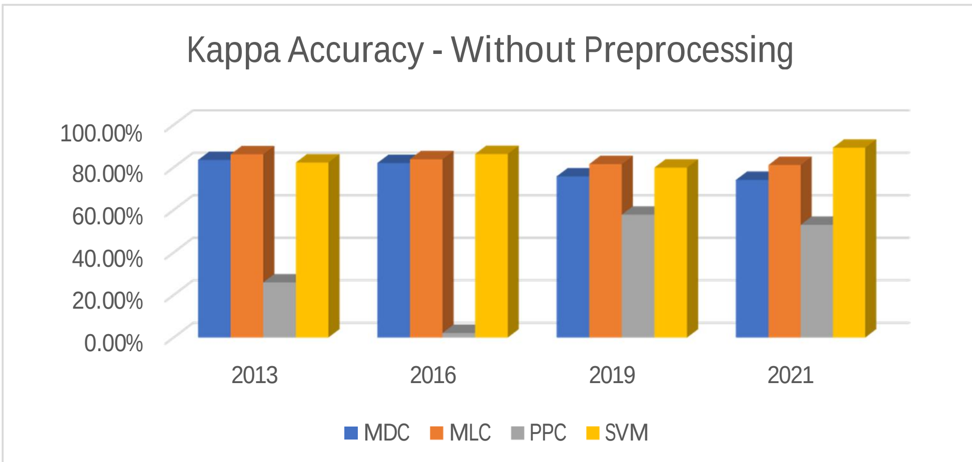
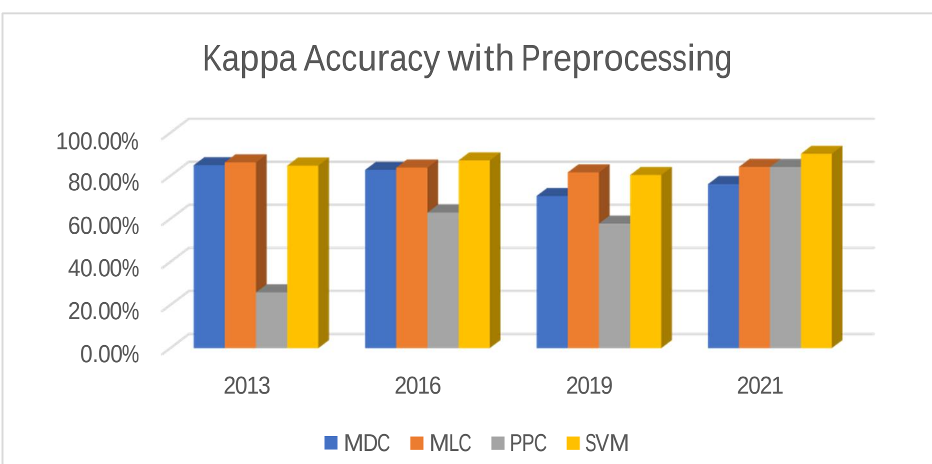


Table 6. Result with Pre-Processing Kappa Accuracy.

	With Processing – Kappa Accuracy			
	2013	**2016**	**2019**	**2021**
Mahalanobis Distance Classification	84.94%	82.77%	70.63%	76.16%
Maximum Likelihood Classification	86.26%	83.84%	81.59%	84.16%
Parallelepiped Classification	25.86%	62.90%	57.77%	84.10%
Support Vector Machine Classification	84.76%	87.19%	80.40%	90.25%



The comparison of table 5th and 6th Kappa accuracy for land use and land cover (LULC) classification before and after pre-processing reveals notable trends. Without pre-processing, Mahalanobis Distance, Maximum Likelihood, and Support Vector Machine classifications display varying accuracy percentages across different years. Parallelepiped Classification, while exhibiting low accuracy without pre-processing, undergoes substantial improvement after pre-processing, with increases ranging from 23.74% to 53.34%. After pre-processing, Mahalanobis Distance, Maximum Likelihood, and Support Vector Machine classifications generally exhibit enhanced accuracy, with percentage improvements ranging from 0.43.% to 5.08.%. These findings underscore the method-dependent nature of pre- processing effects on Kappa accuracy, emphasizing its role in refining the performance of LULC classification models.

IV. RESULT MAPPING AND GROUND TRUTHING

True color images from satellites and sensors in remote sensing mimic Earth's natural colours, serving various purposes in land cover classification, environmental monitoring, urban planning, agriculture, and forestry. These images enhance spatial data analysis, aiding decision-making in various sectors, including crop health assessment and resource management.

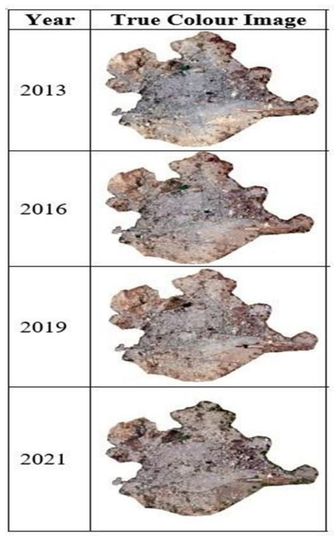


Figure 3. True Color Images 2013, 2016, 2019, and 2021

The mapping of public urban green spaces in Chhatrapati Sambhajinagar City was a comprehensive process using Remote Sensing (RS) and Geographic Information System (GIS) techniques. The process involved data collection, pre-processing, analysis, and validation.

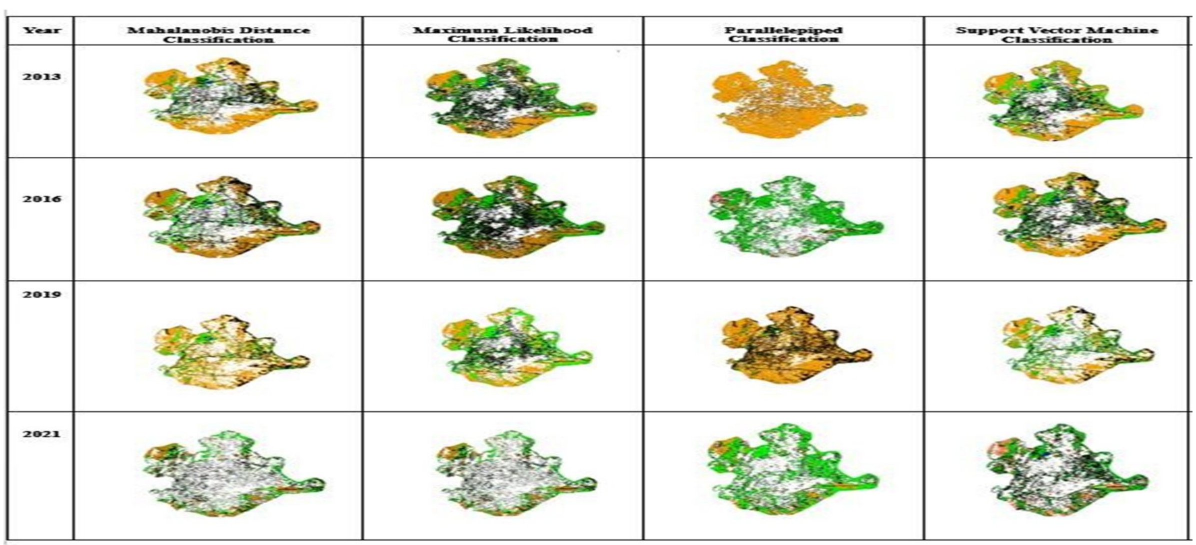


Figure 4. Experimental Result with Pre-Processing with Classified Images 2013, 2016, 2019, and 2021

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Satellite imagery was acquired, and the images were optimized for accuracy. The refined images were then classified using GIS algorithms. The results showed significant improvements in image quality and clarity, facilitating more precise identification and classification of urban green spaces. Ground truthing was conducted to validate the mapping outcomes.

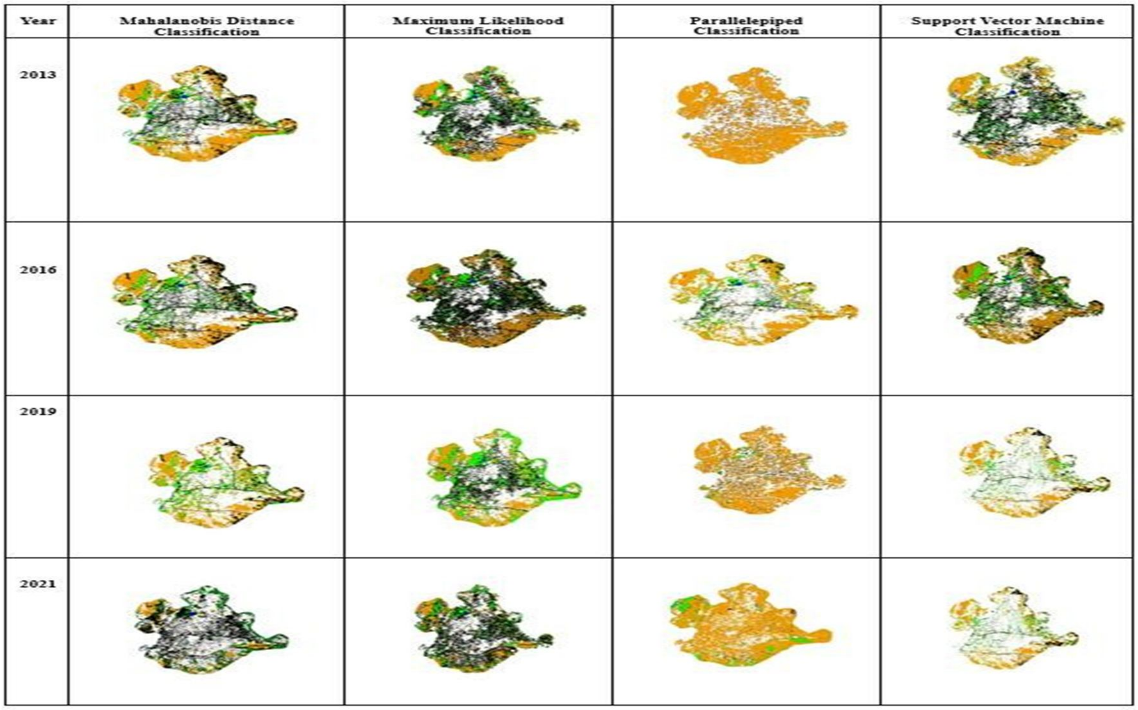

Figure 5. Experimental Result without Pre-Processing Classified images 2013, 2016, 2019, and 2021

The study used Remote Sensing (RS) and Geographic Information System (GIS) techniques to map public urban green spaces in Chhatrapati Sambhajinagar City.

Satellite imagery was obtained and classified using algorithms within the GIS environment, without pre-processing. The results showed the efficacy and limitations of classifying urban green spaces directly from unprocessed satellite imagery. Ground truthing was conducted to validate the results, highlighting the importance of pre-processing steps in enhancing the accuracy and reliability of mapping outcomes in RS-GIS methodologies.

A. Mahalanobis Distance Classification

Is a supervised classification technique used in remote sensing and pattern recognition to assign pixels or data points to predefined classes or categories based on their Mahalanobis distances to the class centroids. This method takes into account both the mean values and the covariance of the data for each class, making it robust to correlations between different features (bands) and allowing for the incorporation of covariance information into the classification process.

$$D_i(x) = \sqrt{(x - m_i)^T \sum_i^{-1} (x - m_i)}$$

Where:

D = Mahalanobis distance

i = the i class

x = n-dimensional data (where n is the number of bands)

Σ_i^{-1} = the inverse of the covariance matrix of a class

m_i = mean ROI of a class

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B. Maximum Likelihood Classification (MLC)

Is a statistical approach used in remote sensing and image processing to classify pixels or objects within an image into predefined classes or categories. It is a supervised classification technique, meaning that it requires a training dataset with known class labels to develop a statistical model for classification. Here's a more detailed explanation of Maximum Likelihood Classification.

$G_i = ln\, p(\omega_i) - \frac{1}{2}$

Where:

i = class

$ln\, |\Sigma_i| - (x-m_i)^T \Sigma_i^{-1} (x-m_i)$

x = n-dimensional data (where n is the number of bands) $\frac{1}{2}$

$p(\omega_i)$ = probability that class ω_i occurs in the image and is assumed the same for all classes

$|\Sigma_i|$ = determinant of the covariance matrix of the data in class ω_i Σ_i^{-1} = its inverse matrix

m_i = mean vector

C. Parallelepiped Classification

Also known as Minimum Distance Classification or Box Classification, is a simple and commonly used supervised classification technique in remote sensing and image processing. It's a straightforward method that classifies pixels in an image into different land cover or land use categories based on their spectral characteristics.

Each class i Pixel 'X' is classified into class 'I' if it falls within the parallelepiped- shaped region defined by the minimum and maximum values for each band (spectral dimension).

$X_j \leq B_{ij} \leq X_j \leq A_{ij}$

Where:

X_j is the pixel's spectral value in band 'j'.

A_{ij} is the maximum threshold value for band 'j' in class'i'. B_{ij} is the minimum threshold value for band 'j' in class 'i'.

D. Support Vector Machine (SVM)

Is a powerful and versatile supervised machine learning algorithm used for classification and regression tasks. It is especially effective for binary and multiclass classification problems.

SVM classification works by finding a hyperplane (decision boundary) that best separates the data into different classes while maximizing the margin between the classes. Here are the key concepts and components of SVM classification: Given a set of training samples (X_i, y), where X_i is the feature vector of sample i is the class label (either +1 or -1), SVM aims to find a hyper plane described by the equation.

$f(X) = (\omega, X) + b$

Where:

X is the feature vector of the input pixel. ω is the weight vector.

b is a bias term.

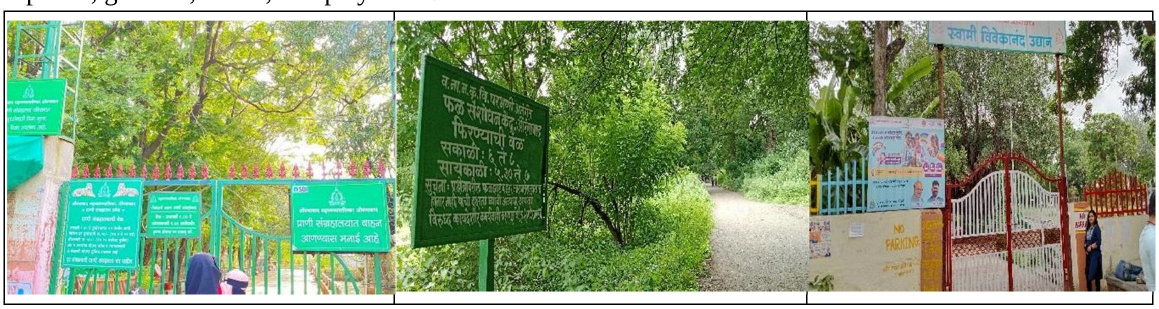
V. GROUND TRUTHING

Table 8th the images captured on the ground for validation and accuracy assessment in the context of land use and land cover classification.

A. Parks and Gardens

Chhatrapati Sambhajinagar Municipal Corporation maintains parks and gardens, with typical layouts including sitting areas, walking trails, kids play areas, green gym sections, open lawns, and shaded yoga platforms.

City parks and gardens feature seating areas, walking trails, kids' play equipment, a green gym, open lawns, And a shaded yoga platform. Green gym and yoga platforms are recent additions, but their placement is Random. Community parks feature water fountains, sculptures, gazebos, lawns, and play areas.



Timing and Instruction Board of Parks and Gardens

B. Playgrounds

Playgrounds in low-vegetation areas lack paved surfaces and courts for sports activities, with few being. Well- maintained, resulting in underutilization in housing areas and neighbourhood playgrounds.

Neighbourhoods lack active recreation facilities, few playgrounds have basketball and badminton courts, and some are unmaintained with peripheral vegetation

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C. Lakes and Revers

Natural lakes in western peripheries, with parks and gardens, cater to a limited population due to access issues and younger generation activities. City lakes are underutilized due to congested surroundings and maintenance issues, while other water bodies are used for sewage and garbage disposal.

The Research includes a promenade of Salim Ali Lake, inner city Kham River, Harsul Lake, and lake front development with kiosks.

D. Urban Forest

The state forest department maintains an urban forest that serves as the city's lungs, offering public access for morning strolls and a community-scale garden for daily recreation.

Reserve forests, urban forest pathways, and community gardens are open for public use, including both indoor and outdoor spaces.
In LULC studies, capturing ground truth images is essential for validating and enhancing the accuracy of remotely sensed or satellite-derived classifications. This process involves physically visiting representative locations within the research area, capturing images that document the actual land cover conditions on the ground. These ground truth images serve as a reliable reference for training and validating classification algorithms, ensuring that the identified land cover classes closely align with real-world conditions. This meticulous validation process contributes to the overall precision and reliability of LULC classification results.

VI. CONCLUSION

In conclusion, our comprehensive analysis of land use and land cover (LULC) classification in Chhatrapati Sambhajinagar City, Maharashtra, India, has shed light on the dynamic urban growth patterns and their implications for climate vulnerability. Leveraging remote sensing and GIS techniques over a nine-year period, our research assessed LULC changes, including Green Area, Buildup Area, Road Area, Water Bodies, and Barren Land. The evaluation of five classification methods highlighted the efficacy of preprocessing techniques in consistently improving classification accuracy, with notable percentage improvements observed in Mahalanobis Distance, Maximum Likelihood, and Support Vector Machine methods. Notably, Parallelepiped Classification demonstrated substantial percentage increases, underscoring the transformative impact of preprocessing on its accuracy. These findings provide valuable insights for urban growth management and climate resilience strategies in rapidly developing urban areas.

VII. FUTURE WORK

Future research endeavors should focus on refining and tailoring preprocessing techniques to better suit the unique characteristics of Chhatrapati Sambhajinagar City and similar urban centers. Further investigation into the specific drivers of LULC changes, such as urbanization and climate-related factors, would enhance our understanding of the observed patterns. Additionally, exploring the temporal dynamics of LULC changes and integrating more recent satellite data can provide real-time insights into urban development trends. The incorporation of machine learning algorithms and advanced statistical models could further enhance the accuracy of LULC classifications. Lastly, a more in-depth exploration of the ecosystem service values (ESV) associated with different LULC categories could contribute to sustainable urban planning by identifying areas of high ecological significance. Overall, ongoing research in these directions will contribute to a more nuanced understanding of urban dynamics and inform proactive strategies for sustainable development and climate resilience.

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