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LULC Classification for Change Detection Analysis of Remotely Sensed Data Using Machine Learning-Based Random Forest Classifier

H N Mahendra[1], V Pushpalatha[2]†, V Rekha [3], N Sharmila[4], D Mahesh Kumar[1], G S Pavithra[5], N M Basavaraj[1], S Mallikarjunaswamy[1]

[1]Department of Electronics and Communication Engineering, JSS Academy of Technical Education, Bengaluru-560060, Karnataka, India. ORCID iD- https://orcid.org/0000-0003-3854-5500

[2]Department of Artificial Intelligence and Data Science, Global Academy of Technology, Bengaluru-560098, Karnataka, India

[3]Department of Computer Science and Engineering, School of Engineering and Technology, Christ University, Bangalore-560060, India.

[4]Department of Electrical and Electronics Engineering, JSS Science and Technology University, Mysuru- 570015, Karnataka, India

[5]Department of Computer Science and Engineering, JSS Academy of Technical Education, Bengaluru-560060, Karnataka, India.

†Corresponding author: V Pushpalatha; pushpav27@gmail.com

ORCID details of the authors: H. N. Mahendra https://orcid.org/0000-0003-3854-5500

ABSTRACT

Land Use and Land Cover (LULC) classification is critical for monitoring and managing natural resources and urban development. This study focuses on LULC classification for change detection analysis of remotely sensed data using a machine learning-based Random Forest classifier. The research aims to provide a detailed analysis of LULC changes between 2010 and 2020. The Random Forest classifier is chosen for its robustness and high accuracy in handling complex datasets. The classifier achieved a classification accuracy of 86.56% for the 2010 data and 88.42% for the 2020 data, demonstrating an improvement in classification performance over the decade. The results indicate significant LULC changes, highlighting areas of urban expansion, deforestation, and agricultural transformation. These findings highlight the importance of continuous monitoring and provide valuable insights for policymakers and environmental managers. The study demonstrates the effectiveness of using advanced machine-learning techniques for accurate LULC classification and change detection in remotely sensed data.

Key Words	Remote Sensing: Multispectral data; Machine learning; Random forest classifier; Linear Imaging Self-Scanning Sensor-III, Land Use Land Cover
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1. Introduction

Land Use and Land Cover (LULC) classification is a crucial aspect of environmental monitoring and management, providing insights into the spatial distribution and temporal dynamics of the Earth's surface (Mahendra, H.N. et al., 2023a). The classification and subsequent change detection of LULC are fundamental for understanding ecological dynamics, urban planning, and resource management (Kumar Jat, M et al., 2008). Traditionally, LULC mapping relied on manual interpretation of satellite images, which was both time-consuming and prone to human error. With advancements in remote sensing technology, it is now possible to acquire high-resolution, multi-temporal satellite imagery, facilitating more efficient and accurate LULC classification (K. Ganesha Raj et al., 2020).

In recent years, the integration of machine learning techniques with remote sensing technologies has emerged as a powerful collaboration, offering unprecedented capabilities for analyzing vast amounts of spatial data (Benyamin Hosseiny et al., 2022; Mahendra, H. N et al., 2023d). This research delves into the application of a machine learning-based random forest classifier for the classification and change detection of remotely sensed data. Remote sensing, with its ability to capture information from a distance, provides an invaluable tool for monitoring changes in the Earth's surface over time (Li, M et al., 2013). Leveraging the efficiency and versatility of machine learning algorithms, particularly the random forest classifier, holds the promise of enhancing the accuracy and automation of such analyses (Chaitanya B. Pande et al., 2022; Jayabaskaran, M. et al., 2023).

The classification of remotely sensed data is a fundamental step in extracting meaningful information about land cover and land use (Belgiu, M et al., 2016). Traditional methods often face challenges in handling the complexity and variability present in large-scale datasets (D. Lu et al., 2007). This research seeks to address these challenges by exploring the random forest (RF) classifier's ability to handle high-dimensional data, nonlinear relationships, and complex interactions between spectral bands. By employing this machine learning approach, we aim to improve the precision and efficiency of land cover classification, leading to more reliable assessments of the Earth's surface characteristics.

Change detection, a critical component of land monitoring, involves identifying alterations in land cover over time (Firoz et al., 2016; Mahendra, H.N et al., 2023b). As environmental dynamics accelerate, timely and accurate detection of changes becomes paramount for informed decision-making (GN Vivekananda et al., 2021). The random forest classifier, known for its adaptability and robustness, presents an innovative solution for change detection in remotely sensed imagery (Gislason et al., 2004; Mahendra, H.N et al., 2023c). Through a systematic analysis of temporal datasets, this research aims to evaluate the random forest classifier's performance in detecting and characterizing land cover changes, contributing to our understanding of environmental transformations on both regional and global scales.

The integration of machine learning algorithms into the realm of remote sensing not only promises advancements in accuracy and efficiency but also opens avenues for scalable and automated analyses (Mahendra H N et al., 2019). By exploring the potential of the random forest classifier in this context, we aspire to contribute to the ongoing discourse on the optimization of land cover classification and change detection methodologies (Tiwari et al., 2024). This research aligns with the broader objective of harnessing technology to address environmental challenges and facilitate sustainable land management practices, ultimately fostering a deeper understanding of our planet's ever-evolving landscape. The outcomes of this research contribute valuable insights into the effectiveness of machine learning-based random forest classifiers for remotely sensed data analysis. The findings have implications for a range of applications, including environmental monitoring, land-use planning, and natural resource management. Eventually, this research enhances our ability to harness the power of machine learning for accurate classification and change detection in remotely sensed datasets, facilitating a more comprehensive understanding of dynamic land cover patterns.

2. Related Works

The use of remotely sensed data in environmental monitoring and analysis has been widely explored in the literature. Numerous studies have investigated the application of various classification techniques to interpret and classify remote sensing data. Notable works include L. S. Davis et al., (2002) and Mahendra, H. N et al., (2023c) who employed Support Vector Machines (SVM) for land cover classification, and Voulgaris et al., (2008), who utilized k-Nearest Neighbors (k-NN) for similar purposes.

A range of studies have demonstrated the effectiveness of random forest classifiers in analyzing remotely sensed data. Piramanayagam et al., (2016) achieved an 86.3% overall accuracy in land cover classification using this method, while Mellor et al., (2014) obtained a 73% accuracy in forest classification. Gislason et al., (2004) further highlighted the potential of random forests in handling multisource data, and Belgiu et al., (2016) emphasized their ability to handle high data dimensionality and multicolinearity. Mosin, V.K et al., (2019) presented tree detection and classification in forestry applications using machine learning. A system with finely tuned filters will make possible robust species classification at a cost much lower than hyperspectral imaging. Boukir, S et al., (2017) used random forest for remote sensing classification. Targeting lower-margin training samples is a strategy for inducing diversity in ensemble classifiers and achieving better classifier performance for difficult or rare classes.

Pal, M. et al., (2005) developed a random forest classifier remote sensing image classification. The number of user-defined parameters required by random forest classifiers is less than the number required for SVMs. Zerrouki, N et al., (2019) presented LULC Change Detection analysis using a machine learning-based algorithm. The proposed detection scheme succeeds in effectively identifying land cover changes. M. Sheykhmousa., et al., (2013) compare the Random forest- and support vector machine-based multi-temporal classifications. Tian, S et al., (2016) used the random forest classifier to achieve accurate classification in the Ertix River in northern Xinjiang, China.

The Random Forest (RF) classifier has proven to be a robust and versatile machine learning algorithm for remote sensing applications. Studies such as Nguyen, H.T et al., (2018) have demonstrated the effectiveness of RF in land cover mapping, showcasing its ability to handle diverse spectral information and improve classification accuracy. Additionally, Shihab, T.H et al., (2020) applied RF to detect changes in land cover over time, showcasing its utility in change detection analyses. Several studies have combined classification and change detection methodologies to monitor environmental changes over time. Abdulhakim Mohamed Abdi et al., (2020) conducted a comprehensive analysis using a combination of machine learning classifiers and change detection algorithms to assess land cover changes in a specific region. Their work highlights the importance of integrating classification techniques with change detection methods for a more comprehensive understanding of dynamic environmental processes.

While the existing literature provides valuable insights into the application of machine learning-based classifiers for remote sensing, there is still a need for research that specifically focuses on the integration of Random Forest classifiers for both classification and change detection tasks. This research aims to address this gap by presenting a detailed analysis of the performance of Random Forest in classifying remotely sensed data and detecting temporal changes, contributing to the advancement of effective environmental monitoring techniques.

3. Study Area

Mysuru district, located in the southern part of the Indian state of Karnataka, is renowned for its rich historical and cultural significance. The district serves as the cultural capital of Karnataka and is steeped in the grandeur of its royal heritage. The city of Mysuru, also known as the 'City of Palaces,' is home to the iconic Mysuru Palace, a splendid architectural masterpiece that attracts tourists from around the world. The palace, built in Indo-Saracenic style, stands as a testament to the opulence and grandeur of the Wadiyar dynasty, which ruled the region for centuries. Apart from the palace, Mysuru is known for its vibrant Dasara festival, celebrated with grandeur, featuring a procession of decorated elephants, cultural events, and a spectacular illumination of the palace.

The district is not just a historical and cultural hub but also boasts a diverse geographical landscape. Nestled in the Deccan Plateau, Mysuru is surrounded by lush greenery, picturesque hills, and serene lakes. The Chamundi Hills, with the Chamundeshwari Temple perched on top, provide a panoramic view of the city. Mysuru is also home to the enchanting Brindavan Gardens, known for its musical fountain and beautifully landscaped terraces. Additionally, the district is recognized for its educational institutions, including the historic Mysore University, contributing to the intellectual and academic development of the region. With its blend of cultural heritage, natural beauty, and educational excellence, Mysuru district stands as a unique and vibrant destination in the heart of South India. The map of the Mysuru district is shown in Fig. 1.

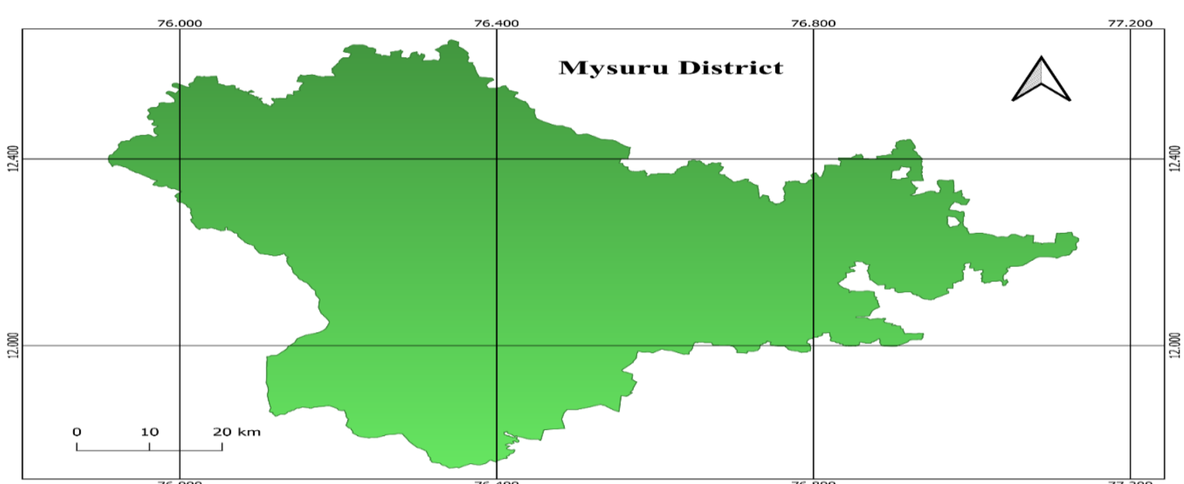

Fig. 1. Study area

4. Data used

Linear Imaging Self-Scanning Sensor-III (LISS-III), is a satellite sensor data used in this work. This sensor is designed for remote sensing applications, particularly in the field of Earth observation. Developed by the Indian Space Research Organization (ISRO), LISS-III is part of the payload onboard the Indian Remote Sensing (IRS) satellites. This sensor operates in the visible and near-infrared spectral bands, capturing high-resolution imagery with a spatial resolution ranging from 23.5 meters to 5.8 meters, depending on the specific satellite and its orbital parameters. The multi-spectral capabilities of LISS-III enable it to provide valuable data for a variety of applications, including agriculture monitoring, land use planning, disaster management, and environmental studies.

One notable aspect of LISS-III is its ability to acquire imagery in multiple spectral bands, such as blue, green, red, and near-infrared. This spectral diversity allows for the extraction of valuable information about the Earth's surface and vegetation health. The high spatial resolution of LISS-III imagery enhances the level of detail in the captured data, making it a valuable tool for precision agriculture, urban planning, and natural resource management. Researchers, government agencies, and industries leverage LISS-III data to make informed decisions and monitor changes in the environment over time, contributing to sustainable development and effective resource utilization. Table 1 provides the details of satellite data used in the study.

Table 1. Satellite Data

Satellite Name	Spatial resolution (meters)	Sensor Used	Year of Acquisition
Resourcesat-1	24m	LISS-III	2010
Resourcesat-1	24m	LISS-III	2020

5. Methodology

LULC classification using RF involves a systematic methodology to accurately categorize different land use and land cover types based on remote sensing data. The first step in the process is data acquisition, where high-resolution satellite imagery is obtained for the study area. These images serve as the input data for the classification model. Preprocessing steps, such as radiometric and atmospheric correction, are performed to enhance the quality of the images and ensure consistency across the dataset. Additionally, feature extraction may be employed to identify relevant spectral, spatial, and textural characteristics that can aid in distinguishing between different land cover classes.

The second step involves the application of the RF algorithm for classification. RF is an ensemble learning technique that combines the predictions of multiple decision trees to improve overall accuracy and robustness. Training data, consisting of labeled samples representing different land cover classes, are used to train the RF model. The algorithm leverages the spectral signatures and spatial patterns present in the training data to build a robust classification model. The model is then applied to the entire dataset, classifying each pixel or image segment into specific land cover categories. Finally, an accuracy assessment is conducted using validation data to evaluate the performance of the RF classifier and refine the model if necessary. This iterative process ensures the generation of reliable and accurate LULC maps for informed decision-making in various applications, such as environmental monitoring, urban planning, and natural resource management. The methodology followed in this research work is shown in Fig. 2.

Data Acquisition: The first step in our methodology involves acquiring remotely sensed data covering the study area. This may include satellite imagery captured at different time points. In this work, we have obtained the LISS-III image of the study area for the years 2010 and 2020 respectively.

Pre-processing: Pre-processing tasks such as atmospheric correction, radiometric calibration, and geometric correction is performed on the both the LISS-III image to enhance the quality of the imagery. Atmospheric correction of satellite data involves removing the effects of the atmosphere such as scattering and absorption) on the reflected light reaching the sensor. This process ensures that the data accurately represents surface reflectance by compensating for atmospheric distortions. Techniques include using radiative transfer models, ground-based measurements, or empirical methods. Corrected data is essential for accurate analysis in remote sensing applications. Radiometric correction of satellite data involves adjusting the pixel values in an image to account for sensor-specific errors, atmospheric conditions, and illumination differences. This ensures that the observed reflectance values represent true ground conditions. The process typically includes calibration using known reference targets and correcting for atmospheric scattering and absorption. It improves the accuracy and consistency of the satellite data for further analysis. Geometric correction of satellite data involves aligning images to a standard coordinate system by correcting distortions due to sensor geometry, satellite motion, and Earth's curvature. This process typically uses ground control points (GCPs) to match the satellite image to a reference map or coordinate system. It ensures accurate spatial representation, making the data usable for further analysis and comparison.

Feature Selection and Extraction: Next, we focus on selecting and extracting relevant features from the remotely sensed data. Feature selection in satellite data typically involves parameters like, spectral bands, in which selection of specific wavelengths relevant to the study (e.g., visible, nir, thermal), spatial resolution is choosing the pixel size that balances detail with computational efficiency, temporal resolution is selecting data from relevant time periods or frequencies of observation, topographic features is inclusion of elevation, slope, and aspect to account for terrain effects, and radiometric calibration is ensuring the data is corrected for sensor and atmospheric influences.

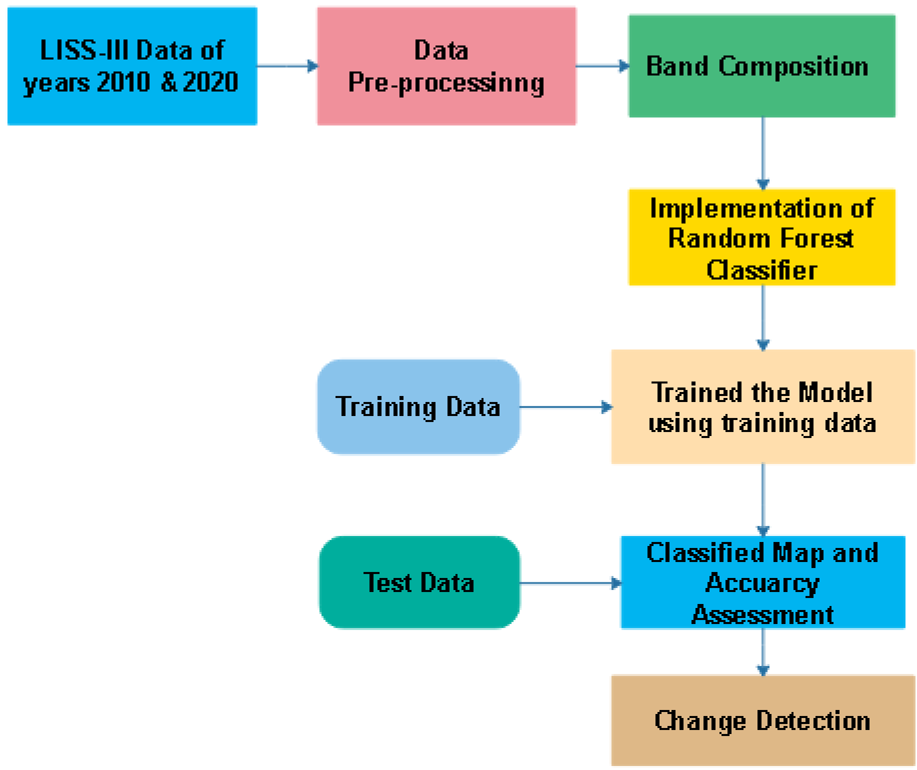

Fig. 2. Methodology

Training Data Collection: A representative set of training data is essential for training the random forest classifier. Ground truth data, collected through field surveys or existing high-quality reference datasets, should be used to label the training samples. These labeled samples should cover the full range of land cover classes present in the study area. Care must be taken to ensure an adequate number of samples for each class, avoiding bias in the classifier towards overrepresented classes.

Random Forest Classification: The heart of our analysis involves the application of a machine learning-based RF classifier to the pre-processed and feature-selected datasets. The classifier will be trained using the labeled training samples, learning the relationships between the selected features and the corresponding land cover classes. The algorithm's ability to handle complex and non-linear relationships makes it well-suited for classifying remotely sensed data. The resulting classification map will provide a detailed representation of land cover types in the study area.

Change Detection Analysis: To detect changes over time, a comparative analysis is performed between classification results from different time points. The classified maps for each time period are compared pixel-wise to identify areas of change. Post-classification change detection techniques may be applied, such as image differencing or the calculation of vegetation indices for change assessment. This step allows for the identification and characterization of land cover changes, such as urban expansion, deforestation, or agricultural land conversion.

Accuracy Assessment and Validation: The final step involves assessing the accuracy of the classification and change detection results. This is done by comparing the classified maps with independent validation datasets or ground truth data not used during the training phase. Accuracy metrics, such as overall accuracy, producer's accuracy, and user's accuracy, are calculated to quantify the reliability of the classification. This step ensures the robustness of the analysis and provides insights into the effectiveness of the random forest classifier in capturing temporal changes in the remotely sensed data.

6. Random Forest (RF) Classifier

RF classifier has emerged as a powerful tool for the classification and change detection analysis of remotely sensed data. In the view of Earth observation, where satellite imagery plays a crucial role, the RF algorithm stands out for its versatility and robustness. Comprising an ensemble of decision trees, RF leverages the principle of bagging (bootstrap aggregating) to construct multiple trees, each trained on a subset of the data. This diversity in the ensemble enhances the model's generalization capabilities, making it well-suited for handling the complex and high-dimensional nature of remote sensing datasets.

In the context of classification, RF excels in distinguishing between land cover classes, a fundamental task in remote sensing applications. The algorithm's ability to consider a multitude of spectral, spatial, and temporal features allows for more accurate and comprehensive classification outcomes. Additionally, the RF model provides information about feature importance, aiding in the interpretation of the classification results and enabling users to understand the key factors influencing land cover distinctions. Change detection, a critical aspect of monitoring environmental dynamics, benefits significantly from the Random Forest classifier. By comparing classifications from different time points, RF can identify changes in land cover with high precision. The ensemble nature of the algorithm enhances its sensitivity to subtle alterations in the landscape, making it particularly effective for detecting land cover changes caused by natural phenomena or human activities.

The RF resistance to overfitting and capacity to handle noisy data contribute to its reliability in remote sensing analyses. The algorithm accommodates a wide range of input data types, such as multispectral or hyperspectral imagery, as well as ancillary information like topographic and meteorological data. This adaptability makes it a versatile choice for various remote sensing applications, from monitoring urban expansion to assessing deforestation. In summary, the RF classifier has proven to be an invaluable tool for classification and change detection analyses of remotely sensed data. Its ensemble-based approach, feature importance insights, and adaptability to different data types contribute to its widespread use in Earth observation studies. Whether applied to monitor land cover changes, map vegetation types, or assess environmental impacts, the RF algorithm stands as a robust and reliable solution in the ever-evolving field of remote sensing. The working principle of the random forest classifier is shown in Fig. 3.

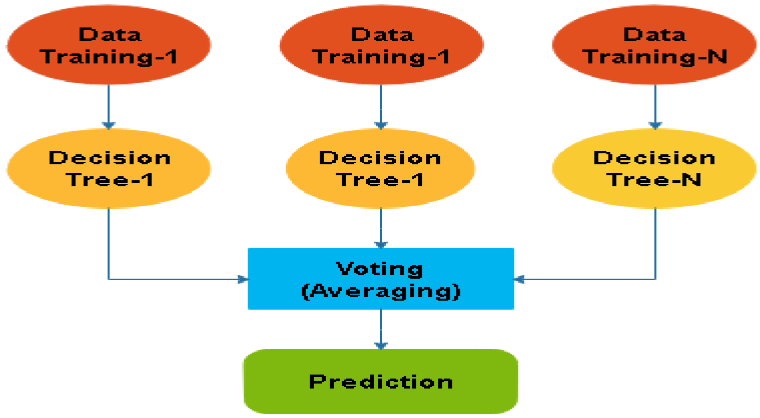

Fig. 3. Working principle of the random forest classifier

Ensemble Learning: Random Forest is an ensemble of decision trees. Ensemble learning combines the predictions of multiple models to improve overall accuracy and robustness. In the case of Random Forest, it builds a forest of decision trees and merges their outputs to make a more informed and reliable prediction.

Decision Trees: Each tree in the Random Forest is a decision tree. Decision trees split the input data based on features, recursively dividing it into subsets until a certain condition is met. The decision at each node is made by evaluating a feature, and the goal is to make the final decision (classification) at the tree's leaf nodes.

Random Feature Selection: Randomness is introduced in Random Forest through the selection of a random subset of features for each decision tree. This helps to decorrelate the trees and avoid overfitting specific features in the dataset. The algorithm doesn't use the entire set of features for each tree, which increases the diversity of the trees in the ensemble.

Bootstrap Sampling: Another source of randomness is introduced through bootstrap sampling, also known as bagging (Bootstrap Aggregating). Random Forest builds each tree on a different subset of the training data, sampled with replacement. This means that some instances may be repeated in the subset, while others may be left out.

Voting or Averaging: Once all the decision trees are built, predictions are made for each tree. In classification, the final prediction is often determined by a majority vote among the trees (for binary classification, it's a simple majority). For regression tasks, the predictions are averaged.

Robustness and Generalization: The combination of multiple trees and the randomness introduced in feature selection and data sampling makes Random Forest robust and less prone to overfitting. It can handle noisy data and outliers better than individual decision trees.

Feature Importance: Random Forest provides a measure of feature importance based on how often a feature is used to split the data across all trees. This can be valuable in understanding the significance of different features in the classification process.

Change Detection Analysis: In the context of change detection, random forest can be applied by training the model on historical data representing different classes (e.g., land cover types) and then using the trained model to classify new or updated data. Changes can be detected by comparing classifications over different time periods.

Overall, the Random Forest classifier's strength lies in its ability to create a robust and accurate model by combining multiple decision trees and introducing randomness through feature selection and data sampling. This makes it well-suited for classification tasks, including change detection analysis in various domains.

7. Results and Discussion

7.1 LULC Classification and Assessment

The study identified and delineated various land cover classes across the study area. The prominent land cover classes included built-up areas, water bodies, cultivated land, fallow land, scrubland, vegetation, and forest. In the analysis of LULC for the year 2010, the classified maps revealed distinctive patterns across various categories. The built-up areas exhibited a significant expansion, indicating urbanization and infrastructure development. Water bodies were identified with precision, reflecting the spatial distribution of lakes, rivers, and other aquatic features. Cultivated lands showcased a mix of agricultural activities, highlighting the regions contributing to food production. Fallow lands, scrub lands, and vegetation were discerned, providing insights into transitional and natural landscapes. Forest cover was evident, emphasizing the importance of preserving biodiversity and ecological balance. The comprehensive classification of LULC in 2010 laid the foundation for understanding the baseline landscape and served as a valuable reference point for subsequent years.

Fast forward to the year 2020, the classified maps depicted dynamic changes in LULC, indicative of evolving environmental and societal factors. Built-up areas exhibited continued expansion, illustrating ongoing urban development. Water bodies maintain their distinct presence, crucial for monitoring aquatic ecosystems and water resource management. Cultivated lands showcased alterations in land use patterns, reflecting changes in agricultural practices. The identification of fallow lands, scrub lands, and vegetation highlighted areas undergoing transition or ecological restoration efforts. Notably, the forest cover exhibited fluctuations, underlining the importance of conservation efforts amidst increasing anthropogenic pressures. The comparative analysis between the 2010 and 2020 classified maps unveiled trends in land use dynamics, providing valuable insights for informed decision-making in the realms of urban planning, environmental conservation, and sustainable resource management. The classified map of the Mysuru district for the years 2010 and 2020 is shown in Fig. 4 and Fig. 5 respectively. The LULC assessment has been carried out for both the classified map and corresponding assessment results of both years is shown in Table 2. The total geographical area of Mysuru district is 6307 sq. km.

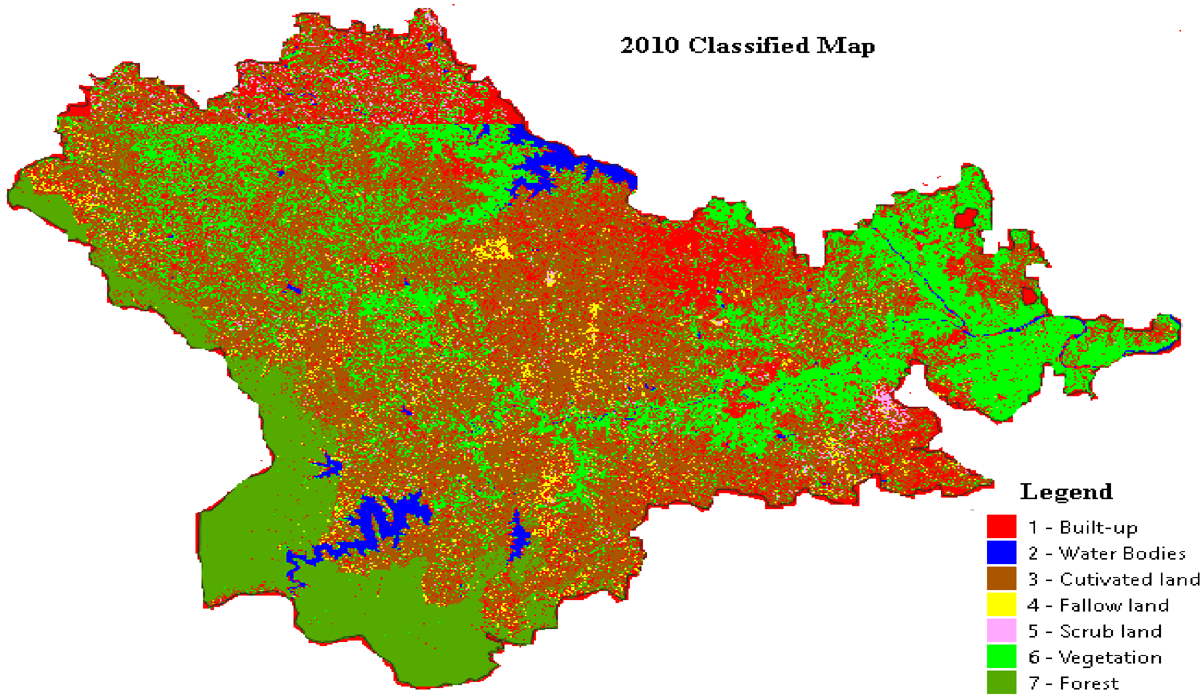

Fig. 4. LULC classified map of the Mysuru district for the year 2010

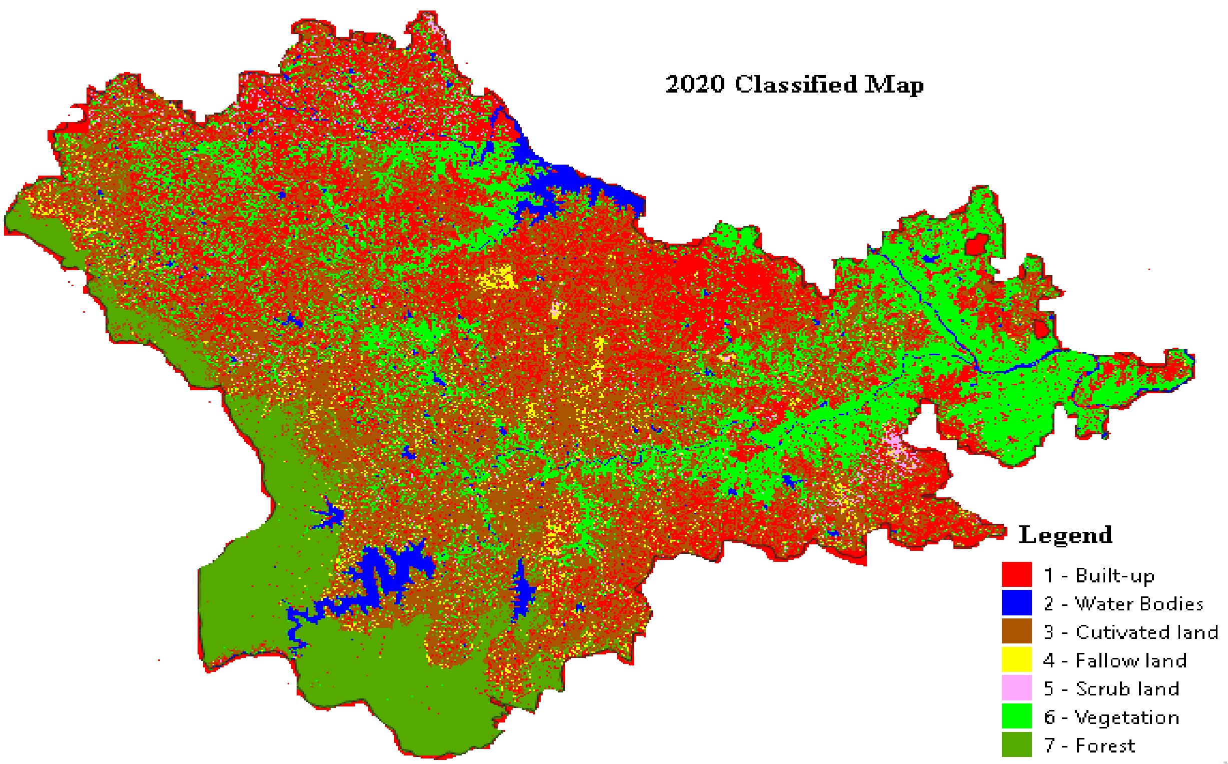

Fig. 5. LULC classified map of the Mysuru district for the year 2020

Table 2. Assessment of LULC classes

Class Name	2010	2020	Change in area (sq. km)
	Area (in Sq. Km)	Area (in sq. Km)	
Built-up	292.24	411.78	119.54
Water bodies	287.55	346.92	59.37
Cultivated land	2986	3751.12	765.12
Fallow land	1096.51	123.26	-973.25
Scrubland	91.6	112.45	20.85
Vegetation	554.4	628.65	74.25
Forest	996.25	932.12	-64.13

7.2 Performance Analysis

The Random Forest classifier demonstrated commendable accuracy in LULC mapping for both time periods. The classification accuracy was measured at 86.56% for the year 2010 and exhibited improvement to 88.42% in 2020 as shown in Table 3. This upward trend in accuracy indicates the robustness of the classification model, suggesting its efficacy in capturing changes in land cover over time. The increase in accuracy from 2010 to 2020 underscores the classifier's ability to adapt and enhance performance, likely attributed to improvements in training data and model optimization. This increase in classification accuracy reflects the effectiveness of the chosen methodology in capturing land use and land cover changes over the decade. The higher accuracy in 2020 suggests the model's ability to adapt to the evolving landscape, highlighting its robustness in handling temporal variations. The other performance parameters such precision, recall, and F1is also calculated for the both the classified images. The Table 3 compares the performance of a RF model using satellite images from two different years, 2010 and 2020 respectively. For 2010 classified data, the model achieved a precision of 85%, recall of 84%, F1 score of 86%, with an accuracy of 86.56% and a Kappa value of 85.86%. While 2020 classified data, the model slightly improved with a precision of 86%, recall of 85%, F1 score of 86%, with a higher accuracy of 88.42% and the same Kappa value of 85.86%.

Table 3. Accuracy assessment results

Model	Satellite Images	Precision	Recall	F1	Accuracy (%)	Kappa Value
RF	LISS-III 2010	85	84	86	86.56 %	85.86%
	LISS-III 2020	86	85	86	88.42 %	86.32%

Further, the performance of the RF classifier is compared with other classification methods as shown in Table 4. The Table 4 compares different classifiers used in studies by various author, focusing on their performance with 2010 and 2020 data. The classifiers listed include Mnlogit model, RAVNet, Deep Learning (DL), Support Vector Machine (SVM), Multilayer Perceptron Classifier (MLC), and Weighted Random Forest (WRF). The comparison results shows that, ours RF provides highest of 88.42%.

Table. 4 Comparison analysis of different classification methods

#	RF		Benyamin Hosseiny et al (2022)	Ram Kumar Singh et al., (2021)	Sudhakar Sengan et al., (2022)	Bryan Sencaki et al., (2023)	Mandla Dlamini et al., (2021)	GN Vivekananda et al., (2021)
Classifier	**2010 Data**	**2020 Data**	**Mnlogit model**	**RAVNet**	**DL**	**SVM**	**MLC**	**WRF**
Accuracy (%)	86.56	88.42	86	81	73.3	82.83	87.46	85.30
Kappa Value	85.86	86.32	NA	NA	NA	0.81	0.857	0.87

7.2 Temporal Changes in LULC

The comparison of LULC maps for 2010 and 2020 revealed significant temporal changes in Mysuru district. Urban expansion, agricultural transformations, and alterations in natural vegetation were notable trends. The increase in classification accuracy facilitated the identification of subtle changes, allowing for a more nuanced understanding of how human activities and natural processes have influenced the landscape over the decade. This insight is crucial for informed land management and sustainable development planning. The analysis of the classified maps reveals significant changes in land use and land cover patterns within Mysuru district over the study period. Urban expansion, agricultural transitions, and alterations in natural land covers are evident. The increase in accuracy not only indicates the model's improved performance but also enhances our understanding of the dynamics shaping the landscape. The identification of specific land cover changes, such as urban encroachment or alterations in vegetation types, can be crucial for informed land management and policy decisions.

7.3 Urbanization and Agricultural Dynamics

The study identified a substantial increase in urban areas, reflecting the rapid pace of urbanization in Mysuru district. This expansion is evident in the conversion of agricultural land and natural vegetation to built-up areas. Conversely, certain regions experienced agricultural intensification, possibly indicating shifts in crop patterns or land management practices. The Random Forest classifier proved effective in distinguishing between these land cover types, providing valuable information for urban planning, agricultural policy, and environmental conservation efforts.

7.4 Implications for Sustainable Land Management

The accurate classification of LULC in the Mysuru district using the random forest classifier has important implications for sustainable land management and urban planning. The identification of areas experiencing rapid change allows policymakers to target conservation efforts or plan for infrastructure development. The observed trends in land use and land cover alterations can inform strategies to mitigate environmental impacts and promote sustainable practices. This study provides a valuable foundation for ongoing monitoring efforts and emphasizes the importance of regularly updating land cover classifications to capture dynamic changes in the landscape.

7.5 Challenges and Limitations

Despite the overall success of the RF classifier, some challenges were encountered during the classification process. These challenges included the presence of spectral confusion in certain land cover classes and the need for careful consideration of spectral signatures. Additionally, cloud cover and atmospheric conditions in the satellite imagery posed constraints, emphasizing the importance of preprocessing techniques to mitigate these effects. Addressing these challenges is crucial for further improving the accuracy and reliability of LULC classifications. The resolution of the satellite data used in this study is 23.5m. However, classification accuracy can be further improved using of high-resolution data.

7.6 Implications and Future Directions

The results of this study have implications for land management, environmental monitoring, and urban planning in Mysuru district. The high accuracy achieved by the Random Forest classifier underscores its suitability for mapping and monitoring land cover changes. Future research should explore the integration of additional data sources, such as multi-sensor satellite imagery or ancillary data, to enhance classification accuracy further. Additionally, employing advanced machine learning techniques and incorporating ground-truth data could contribute to a more comprehensive understanding of the dynamic LULC patterns in the region.

8. Conclusion

This research has demonstrated the efficiency of employing a machine learning-based random forest classifier for the classification and change detection of remotely sensed data. The utilization of a robust random forest algorithm has allowed for accurate and efficient classification of land cover classes, providing a valuable tool for applications such as environmental monitoring, urban planning, and resource management. The findings of this study show the importance of leveraging machine learning techniques, particularly the random forest classifier, in the field of remote sensing. The classifier achieved a classification accuracy of 86.56% for the 2010 data and 88.42% for the 2020 data, demonstrating an improvement in classification performance over the decade. The achieved high classification accuracy and sensitivity to temporal changes highlight the potential of this methodology for addressing the challenges associated with analyzing large-scale and dynamic environmental datasets. Future research could explore additional refinements and extensions of this methodology, as well as its application to different geographic regions and environmental contexts, to further advance the capabilities of machine learning in remote sensing applications.

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