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Research Article

Application of GIS and Remote Sensing to Study the Change Detection in Similipal Reserve Forest using Machine Learning

Arpita Majhi[1], Mrutyunjaya Panda[1], Kabir Mohan Sethy[2]
[1]*Department of Computer Science and Application, Utkal University, Bhubaneswar, Odisha*
[2]*Department of Geography, Utkal University, Bhubaneswar, Odisha*

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ABSTRACT

This research paper explores how Geographic Information Systems (GIS), remote sensing techniques, also machine learning algorithms apply to detect change in the Similipal Reserve Forest. The primary objectives involve analysing spatial together with temporal variations within vegetation cover as well as assessing fluctuations for water body dynamics inside of the forest area. The study integrates GIS data with remote sensing data because it uses regression analysis to measure trends during this period. Spectral indices from satellite imagery are specifically used in assessing vegetation density changes. In contrast, water indices are employed for analysis of variations in water bodies. Important shifts in water body extent and vegetation cover emerge from the study. These alterations do indicate dynamic ecological processes within the Similipal Reserve Forest. The paper underscores that in order to conserve the forest's ecological integrity and also biodiversity, monitor and manage with effectiveness continuously. Furthermore, the research recommends that future studies integrate advanced machine learning algorithms for improved accuracy and efficient change detection. This study adds knowledge in a general way to the increasing application of GIS, remote sensing, and machine learning when it comes to ecological research plus natural resource management.

Keywords: Change detection, Geographic Information System, Machine learning, Remote sensing.

1. Introduction

The Similipal Reserve Forest, located in the Mayurbhanj district of Odisha, India, stands as one of the country's most significant biodiversity hotspots and is recognized globally for its huge ecological diversity and unique flora and fauna. Spanning an area of approximately 2,750 square kilometres, the forest reserve surrounds diverse habitats ranging from lush tropical forests to grasslands, making it a haven for numerous plant and animal species, including several endangered ones. However, like numerous other natural ecosystems worldwide, the Similipal Reserve Forest is facing unprecedented challenges due to anthropogenic activities, climate change, and natural disturbances. These features have led to considerable alterations in the forest landscape, including changes in vegetation cover and variations in water body dynamics. Such changes not only impact the ecological balance of the forest but also have far-reaching implications for local communities dependent on its resources for their livelihoods. In light of these challenges, there is an intense need for comprehensive and systematic monitoring of the Similipal Reserve Forest to understand the extent and nature of changes occurring within its boundaries. Geographic Information Systems (GIS) and remote sensing technologies provide powerful tools for such monitoring, providing spatially explicit data and enabling the analysis of landscape changes over time. Moreover, the integration of machine learning algorithms with GIS and remote sensing techniques holds immense potential for automated and accurate detection of changes in forest ecosystems. This study encounters with following objectives, to analyse the spatial and temporal changes in vegetation cover within Similipal Reserve Forest using GIS and remote sensing data, integrating regression analysis to quantify trends over time. It assesses the changes in water body dynamics within the Similipal Reserve Forest region through remote sensing techniques, employing regression analysis to characterize the relationship between spectral signatures and temporal variations in water extent. This research paper aims to come up with the ongoing efforts to monitor and manage the Similipal Reserve Forest by employing a multidisciplinary approach that combines GIS, remote sensing, and machine learning methodologies. Specifically, the study focuses on analyzing changes in vegetation cover and water body dynamics within the forest area over a particular time period. By delineating and quantifying these changes, the research looks for valuable insights into the drivers of ecosystem dynamics in the Similipal Reserve Forest, henceforth informing conservation and management strategies for this invaluable natural asset.

2. Literature Review

Reis (2008) investigated the shifting landscape of Rize through the application of Remote Sensing and GIS methodologies. Employing satellite imagery and spatial analysis, the study aims to analyse and map land use land cover changes over a specific timeframe. The research's significant outcomes include providing crucial insights into the dynamic patterns of these changes, offering valuable information for informed decision-making in sustainable land management and urban planning in North-East Turkey. By effectively integrating remote sensing and GIS technologies, the study contributes to a comprehensive understanding of the evolving landscape, with potential implications for grographical development and environmental conservation.

Xiong et al. (2016) generated a nominal 30-meter resolution Cropland Extent Map for Continental Africa by integrating pixel-based and object-based algorithms. Using Sentinel-2 and Landsat-8 data on Google Earth Engine, the research seeks to improve the accuracy and efficiency of cropland mapping across the vast African continent. The methodology entails the integration of pixel-based and object-based algorithms, utilizing multi-sensor satellite data from Sentinel-2 and Landsat-8. The approach incorporates the capabilities of Google Earth Engine, a cloud-based platform, to streamline data processing and analysis. The fusion of these techniques enables a comprehensive and accurate assessment of cropland extent at a nominal 30-meter resolution. The study contributed a high-resolution Cropland Extent Map for Continental Africa, providing a valuable resource for agricultural monitoring, land-use planning, and food security assessments. The amalgamation of diverse satellite data sources and latest algorithms enhances the precision of cropland mapping, offering a crucial tool for policymakers, researchers, and practitioners involved in agriculture and land management across the African continent.

Praveen et al. (2019) estimated the portability of machine learning algorithms in the context of agricultural land use land cover mapping, employing cloud computing resources and Earth observation datasets. By leveraging machine learning techniques and scalable cloud infrastructure, the research assesses the adaptability of models across diverse geographic regions. The outcomes aim to shed light on the potential for effective, widely applicable mapping methodologies in agriculture, emphasizing the significance of scalability and generalization capabilities in the development of robust and adaptable machine learning models for precision farming and sustainable land management.

Snic et al. (2020) focused on implementing an object-oriented Land Use Land Cover (LULC) classification approach utilizing Google Earth imagery and learning algorithms. The primary objective is to enhance the accuracy and interpretability of LULC mapping by grouping pixels into meaningful objects based on spectral, spatial, and contextual information. The study aims to produce a refined and contextually relevant classification map, particularly beneficial in urban and complex landscapes, where object-oriented methods can provide a more detailed understanding of land use patterns and changes.

Amani et al. (2020) analysed into the extensive applications of the Google Earth Engine (GEE) cloud computing platform in handling Remote Sensing Big Data. Investigating its functionalities and tools, the study explores how GEE enables large-scale processing and analysis of remote sensing datasets, offering insights into its impact on diverse areas such as environmental monitoring, land cover change analysis, and ecosystem assessment. By synthesizing current knowledge, the review aims to provide a comprehensive understanding of GEE's role in overcoming computational challenges and advance research and decision-making tasks in the era of Remote Sensing applications.

Phan et al. (2020) investigated land cover classification using Google Earth Engine (GEE) and the Random Forest classifier, focusing on the significant role of image composition in improving accuracy. Leveraging the cloud-based processing capabilities of GEE, the research systematically explores various arrangements of spectral bands, indices, and temporal sequences to assess their consequence on classification outcomes. The objective is to identify the most efficient image framework that optimize the Random Forest classifier's performance for accurate and exhaustive land cover mapping. The study's outcomes are anticipated to contribute valuable insights to refining classification methodologies and enhancing the precision of land cover assessments through efficient utilization of satellite imagery within the GEE platform.

Brovelli et al. (2020) used multi-temporal remote sensing data and machine learning classification on the Google Earth Engine platform to monitor forest change in the Amazon. Leveraging the capabilities of GEE, the research applies advanced machine learning algorithms to analyse historical data, detect patterns, and classify temporal changes in Amazonian forest cover efficiently. The anticipated outcomes aim to provide a comprehensive understanding of deforestation, afforestation, and overall landscape dynamics in the Amazon, contributing valuable insights for informed conservation and management strategies in the face of ongoing environmental challenges.

Pratic et al.(2021) employed machine learning classification within Google Earth Engine to analyze Mediterranean forest habitats using seasonal Sentinel-2 time-series data. The primary objective is to optimize input image composition, systematically exploring spectral bands, indices, and temporal sequences to enhance classification accuracy. By leveraging the rich information captured in Sentinel-2 time-series, the research aims to provide a nuanced understanding of the temporal dynamics of Mediterranean forest ecosystems. The anticipated outcomes include improved habitat classification, offering valuable insights into seasonal variations and distinctive features of these habitats, ultimately contributing to enhance monitoring and management strategies for Mediterranean forests.

Tassi et al. (2021) delved into Landsat 8 data classification within Google Earth Engine using the Random Forest algorithm, comparing pixel-based and object-based approaches in the context of Maiella National Park. The primary aim is to assess the efficacy of these methods in accurately delineating land cover. By systematically evaluating their performance, the research contributes insights into the suitability of pixel and object-based techniques, offering valuable guidance for optimal classification approaches in similar ecosystems. The outcomes are anticipated to inform future remote sensing applications and conservation strategies within Maiella National Park and comparable regions.

Shetty et al. (2021) evaluated the influence of training sampling design on the efficacy of machine learning classifiers for land cover mapping using multi-temporal remote sensing data on Google Earth Engine. Through a systematic exploration of diverse sampling strategies, encompassing spatial distribution, temporal representation, and sample size, the research aims to comprehensively assess how variations in training sample selection impact accuracy valuable insights into optimal sampling strategies, providing guidance to enhance the performance and generalizability of machine learning classifiers for effective and nuanced land cover mapping in dynamic environmental contexts.

Feizizadeh et al. (2023) employed machine learning data-driven approaches within Google Earth Engine for comprehensive land use land cover mapping and trend analysis. Utilizing advanced algorithms and multi-temporal satellite imagery, the research aims to produce accurate land use land cover maps while also conducting temporal trend analyses to unveil dynamic landscape changes over time. Leveraging the cloud-based capabilities of Google Earth Engine, the anticipated outcomes include high-precision land cover classifications and valuable insights into evolving patterns, providing a foundation for informed decision-making in resource management, urban planning, and environmental conservation.

Murtiyoso et al. (2024) examined the evolving landscape of virtual forests by investigating the use and application of three-dimensional (3D) data in forestry. Focusing on advancements in remote sensing, LiDAR technology, and other data sources, the study identifies emerging questions, challenges, and opportunities associated with leveraging virtual representations of forests for enhanced monitoring and management. By synthesizing existing literature and research, the review aims to provide valuable insights into the current state of 3D data utilization in forestry, guiding future research directions and informing strategies for optimizing the application of virtual forests in forest management and conservation practices.

The present study aligns with the existing literature on the integration of geospatial technologies and machine learning for monitoring and analyzing forest dynamics, particularly within the Similipal Reserve Forest.

Previous research has underscored the effectiveness of GIS and remote sensing in capturing spatial information, while machine learning techniques offer advanced capabilities for change detection and classification, as exemplified in related studies. The amalgamation of GIS, remote sensing, and machine learning methodologies enables a more comprehensive understanding of land cover changes, facilitating effective forest management strategies. This research contributes to this evolving field by specifically focusing on the Similipal Reserve Forest, employing a machine learning approach for change detection, and providing valuable insights into the application of geospatial technologies in forestry research.

Although extensive research has been conducted on the integration of GIS and remote sensing for change detection in forests, a notable research gap exists in the specific context of the Similipal Reserve Forest regarding the utilization of machine learning techniques. Limited studies have explored the application of advanced machine learning algorithms to analyze temporal changes within the Similipal Reserve Forest, which is essential for addressing its unique challenges and complexities. The research gap emphasizes the necessity for a focused investigation that leverages machine learning for change detection in the Similipal Reserve Forest, considering its distinct characteristics and dynamics. The present study in this area aims to provide valuable insights into the effectiveness and efficiency of machine learning models in capturing nuanced changes in land cover within the Similipal Reserve Forest, contributing to the broader understanding of the applicability of advanced geospatial technologies in regional forest management and conservation efforts.

3. Methodology:

3.1 Data Collection and Pre-processing:

The methodology begins with the acquisition of multi-temporal satellite imagery covering the Similipal Reserve Forest area. High-resolution imagery from sources such as Landsat and Sentinel-2 is accumulated for multiple time points spanning the study period (Tsionas, 2002). Additionally, ancillary data, including digital elevation models (DEMs) and land cover maps, are obtained to augment the analysis. All datasets are carefully processed to ensure compatibility and consistency, including geometric correction, atmospheric correction, and radiometric calibration (Beck & Katz, 1995).

3.2 Vegetation Cover Analysis:

To analyse changes in vegetation cover, spectral indices such as Normalized Difference Vegetation Index (NDVI) and Enhanced Vegetation Index (EVI) are calculated from the pre-processed satellite imagery (Sharma & Yu, 2015). These indices serve as substitutes for vegetation density and health, allowing for the detection of temporal variations in vegetation cover. Regression analysis is then applied to model the relationship between spectral indices and ground-based vegetation measurements, facilitating the estimation of vegetation density changes over time (Mukherjee et al., 2014).

3.3 Machine Learning Integration:

To enhance the accuracy and efficiency of change detection analyses, machine learning algorithms are integrated into the procedures. Supervised classification algorithms, such as Random Forest and Support Vector Machine (SVM), are trained on labelled training datasets to classify land cover types and detect changes over time. Additionally, unsupervised clustering techniques, for instance as K-means clustering, may be utilized to identify spatial patterns and clusters of change within the forest area (Nathans et al., 2012).

3.4 Validation and Accuracy Assessment:

The methodology includes a rigorous validation process to assess the accuracy of the change detection results. Ground truth data collected through field surveys and high-resolution imagery are compared with the classified change maps to assess the reliability and precision of the methodology. Statistical estimates such as accuracy, precision, and kappa coefficient are calculated to quantify the performance of the change detection algorithms (Wagner & Shimshak, 2007).

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4. Data Analysis and Result:

Finally, the processed data and analysis results are comprehensively analysed to derive meaningful insights into the dynamics of vegetation cover and water bodies within the Similipal Reserve Forest. Spatial and temporal patterns of change are identified, and their potential drivers, including natural processes and human activities, are interpreted to inform conservation and management approaches. The application of GIS and remote sensing techniques in conjunction with machine learning algorithms facilitated a comprehensive analysis of forest cover changes within the Similipal Reserve Forest. Through the processing and analysis of satellite imagery spanning a specific period, the study yields several significant findings. Table 1 presents the classification accuracy for different land cover types.

Table 1: Classification Results for Land Cover Types

Land Cover Type	Classification Accuracy (%)
Dense Forest	93
Open Forest	97
Water	100
Crop_Land	91
Settlement Area	94
Waste_Land	85

The results indicate high accuracies across all categories, with water bodies achieving the highest accuracy of 100%, followed closely by Open Forest and Settlement Areas at 97% and 94%, respectively. Dense Forest, Crop Land and Waste Land areas also demonstrate strong classification performance, with accuracies of 93%, 91%, and 85%. Overall, the table suggests that the applied classification techniques, likely using machine learning algorithms such as Support Vector Machine (SVM) or Random Forest (RF), effectively differentiate between various land cover types within the study area. The Land Use and Land Cover Classification of SRF using Random Forest algorithm in the year (a) 2014 (b) 2016 (c)2018 (d) 2020 (e) 2022 is shown in the figure 1.

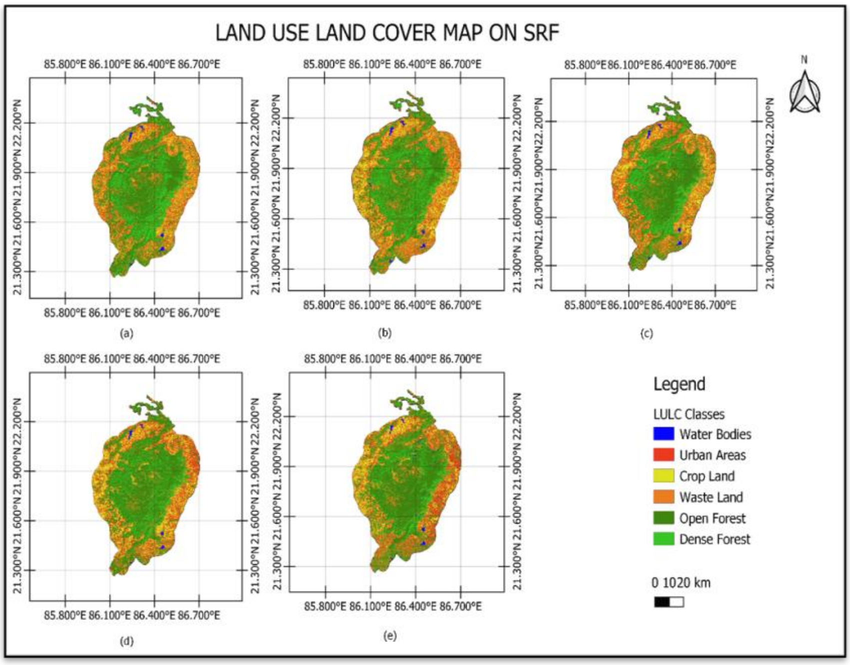

Figure 1: Land Use and Land Cover Classification of Similipal Reserve Forest (SRF) using Random Forest algorithm in the year (a) 2014 (b) 2016 (c)2018 (d) 2020 (e) 2022

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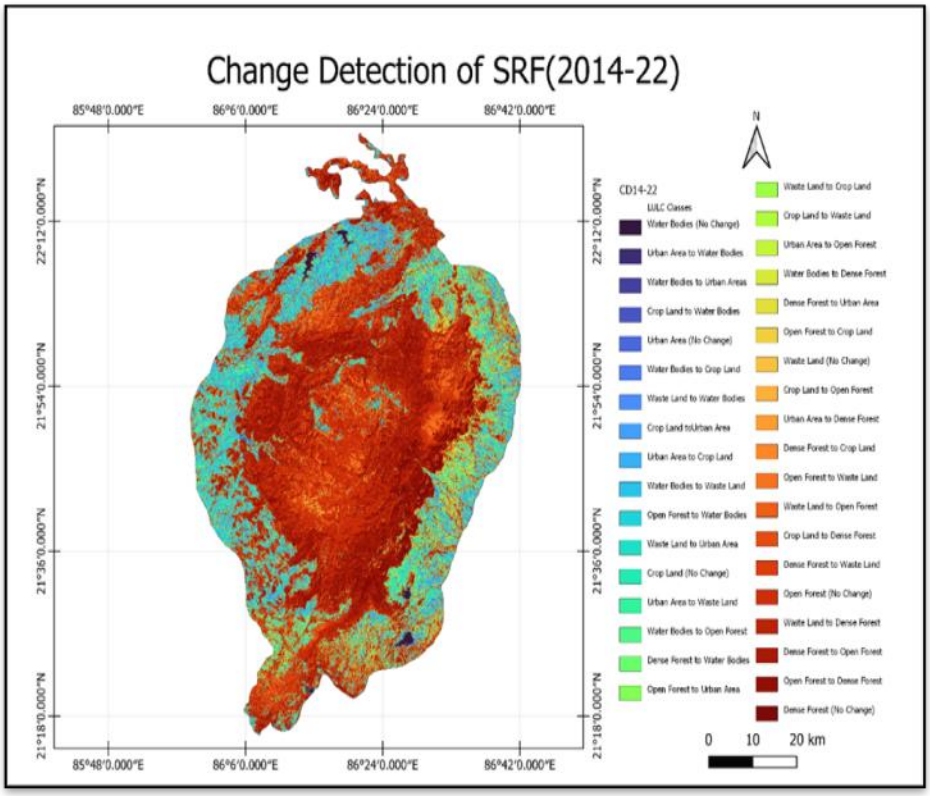

Figure 2: Change Detection Map of Similipal Reserve Forest (SRF) from 2014-2022 in QGIS

The Changes in the images of Similipal Reserve Forest in the year 2014 to 2022 is shown in the form of map which is generated from QGIS is represented in figure 2. The Change Detection graph is represented from the map is shown in figure 3.

The initial step involved the learning and development of multi-temporal satellite images covering the study area. These images were pre-processed to enhance their quality and eliminate any atmospheric changes or sensor-related anomalies. Subsequently, image classification techniques were employed to categorize the land cover types within the forest area. Supervised classification methods, including Support Vector Machine (SVM) and Random Forest (RF), were utilized to accurately delineate various land cover classes such as dense forest, sparse vegetation, water bodies, agricultural land, and built-up areas. The classification results revealed substantial changes in forest cover over the study period. A comparative analysis of the land cover maps generated for different time intervals indicated a noticeable decrease in the extent of dense forest areas, accompanied by an increase in non-forest land cover classes. The spatial distribution of these changes varied across different regions within the Similipal Reserve Forest, with certain areas experiencing more pronounced alterations compared to others.

Moreover, the amalgamation of ancillary data such as historical land use records, climatic variables, and terrain attributes enhanced the interpretation of forest change dynamics. Correlation analysis between these variables and observed changes in forest cover further explain the underlying drivers of deforestation and land degradation processes within the Similipal Reserve Forest. Overall, the results of the study contribute to a better understanding of the spatiotemporal dynamics of forest cover change in the Similipal Reserve Forest.

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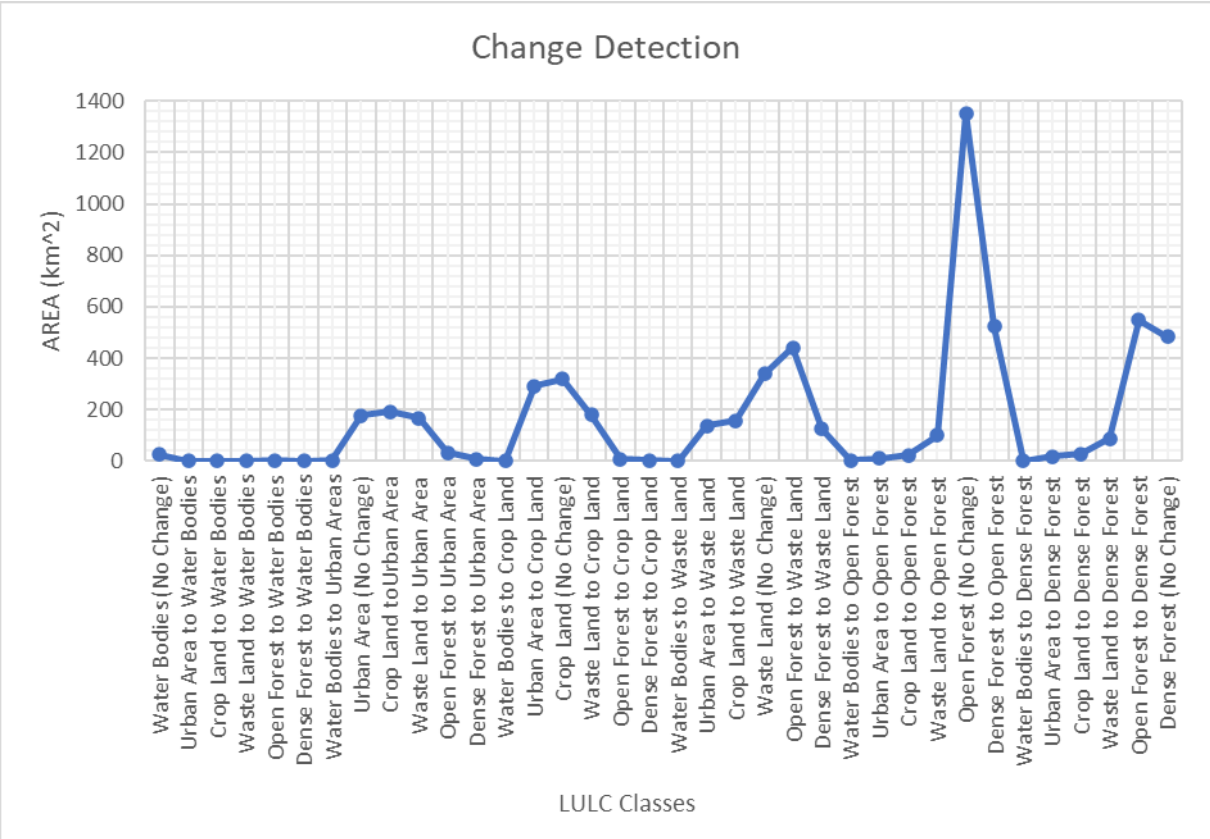

Figure 3: Change Detection graph Similipal Reserve Forest from 2014-2022

The findings underscore the importance of utilizing advanced geospatial technologies and machine learning approaches for accurate and timely monitoring of forest ecosystems, thereby informing sustainable forest management practices and conservation strategies. The application of GIS, remote sensing, and machine learning techniques provided comprehensive insights into the dynamics of forest cover change within the Similipal Reserve Forest. This section discusses the key findings of the study and provides a detailed analysis of their implications for forest management and conservation efforts. The analysis of multi-temporal satellite imagery revealed notable changes in the extent and composition of forest cover over the study period. The classification results depicted a decline in dense forest areas, accompanied by an expansion of non-forest land cover types. This trend aligns with broader concerns regarding deforestation and habitat loss, which are exacerbated by anthropogenic activities such as logging, agricultural expansion, and urbanization.

5. CONCLUSION

The comprehensive analysis of forest cover change in the Similipal Reserve Forest utilizing GIS, remote sensing, and machine learning techniques offers valuable insights into the dynamics, drivers, and implications of forest degradation. This section briefly summarizes the key findings of the study and outlines implications for forest management, conservation, and future research directions. The study discerned essential changes in forest cover over the study period, marked by a decline in dense forest areas and an expansion of non-forest land cover types. These transformations stem from a blend of biophysical and environmental change factors, encompassing land conversion for agriculture, logging, urbanization, and infrastructure development. Spatial analysis unveiled spatial heterogeneity in forest cover change, underscoring the importance of targeting conservation efforts and prioritizing areas for intervention. Temporal analysis revealed both short-term changes and long-term trends in forest cover dynamics. While short-term variations, like seasonal changes and periodic events such as wildfires, contribute to observed variability, long-term trends highlight persistent drivers of forest loss, emphasizing the necessity for sustained monitoring and management efforts to address underlying causes. Demonstration of the effectiveness of machine learning algorithms in accurately classifying land cover types and detecting forest change is underscored by high classification accuracies and reliable change detection results. In spite of several limitations and uncertainties associated with remote sensing data, applied methodologies offer a robust framework for regional-scale forest monitoring. Moreover, amalgamation of ancillary data such as climate variables and socio-economic indicators enriches understanding of forest cover change drivers. Correlation analysis reveals significant relationships between forest loss and factors such as population density, land tenure systems, and climatic variables, spotlighting the complex socio-ecological dynamics driving forest dynamics. The study's implications for forest management and conservation are manifold. Identification of areas at high deforestation risk and understanding underlying drivers enables policymakers and land managers to come up with significant actions to mitigate forest loss and promote regeneration. Strategies like protected area expansion, sustainable land use planning, community-based conservation initiatives, and policy interventions are critical for safeguarding forest ecosystem's ecological integrity. Furthermore, interdisciplinary collaboration and stakeholder engagement are underscored in addressing forest conservation challenges. Holistic approaches to forest management balancing conservation goals with socio-economic needs can be developed by integrating ecological, social, and economic perspectives. These findings contribute to the significant knowledge on forest dynamics and provide evidence-based insights for informing conservation strategies and sustainable land management practices. Continued research efforts and technological advancements are crucial for monitoring forest ecosystems' health and resilience amidst ongoing environmental change and human pressures, ensuring their long-term viability and provision of ecosystem services for future generations.

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