
Tropical Forest Degradation: A Survey of Remote Sensing Technologies and Ecological Impacts

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Abstract

Tropical forest degradation, characterized by the deterioration of forest ecosystems, poses significant ecological and climatic challenges, impacting biodiversity, carbon storage, and ecosystem stability. This survey paper examines the critical role of remote sensing technologies in monitoring and understanding these changes. Advanced tools such as LiDAR, high-resolution imagery, and UAVs provide comprehensive insights into forest structure and dynamics. The integration of these technologies with machine learning techniques enhances the accuracy of forest fragmentation assessments, ecological succession, and deforestation impacts. Case studies highlight the practical applications of remote sensing in biomass estimation, forest fire prediction, and biodiversity assessment, demonstrating the transformative potential of these innovations in forest management. Despite the advancements, challenges remain, including data accuracy, computational limitations, and sensor constraints. Addressing these requires ongoing research and development to enhance remote sensing capabilities and integrate diverse data sources effectively. Future directions emphasize technological advancements, such as improved data fusion techniques and efficient computational models, to overcome current limitations and support sustainable forest conservation efforts. This comprehensive survey underscores the indispensable role of remote sensing in mitigating tropical forest degradation and guiding effective conservation strategies.

1 Introduction

1.1 Significance of Tropical Forest Degradation

Tropical forests are crucial for global biodiversity and carbon sequestration, yet they face escalating threats from deforestation and degradation [1]. The urgent need to understand tropical forest degradation is highlighted by alarming rates of forest dieback, which indicate declining ecosystem health through widespread loss of tree foliage [2]. For instance, Borneo has witnessed a 62% reduction in old-growth forests over the past four decades, despite its status as a biodiversity hotspot and carbon-rich region [3].

Effective management and conservation strategies hinge on precise mapping and monitoring of these forests, as evidenced by studies on indigenous and plantation forests in South Africa [4]. Remote sensing technologies, particularly LiDAR, are instrumental in revealing tree species composition and biomass, essential for grasping forest ecosystem dynamics and enhancing management practices [5]. Furthermore, understanding fire dynamics and edge effects is vital for preserving biodiversity and ecological integrity [6].

The degradation of tropical forests not only threatens biodiversity but also disrupts global climate systems by altering carbon and water cycles. Addressing biodiversity loss and climate change necessitates the utilization of advanced remote sensing technologies, including thermal infrared detectors and superpixel segmentation methods, alongside comprehensive ecological studies. These innovations enable precise monitoring of endangered species and deforestation, fostering sustainable

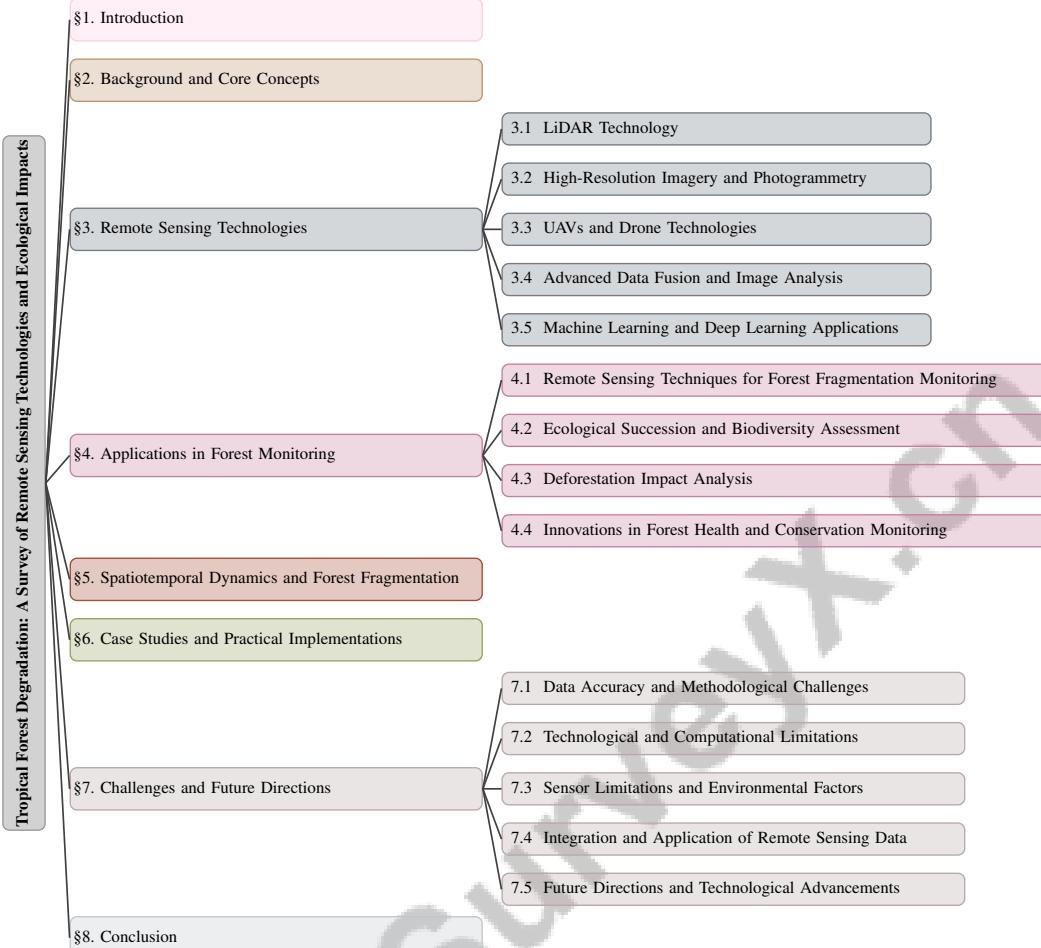


Figure 1: chapter structure

conservation practices and climate change mitigation strategies. By tackling challenges related to data accuracy and detection capabilities, we can enhance conservation efforts and respond more effectively to global ecosystem threats [1, 7, 8, 9, 10].

1.2 Role of Remote Sensing Technologies

Remote sensing technologies are integral to the study and monitoring of forest ecosystems, providing tools that deepen our understanding of forest dynamics and health. High-resolution remote sensing products, including aerial imagery and LiDAR, facilitate detailed assessments of forest structure and dynamics [11]. Airborne Laser Scanning (ALS) exemplifies this, enabling precise mapping of forest structural properties across extensive areas [3].

Drones have transformed forest monitoring by allowing rapid and safe coverage of large areas, essential for timely evaluations of forest conditions [10]. The emergence of low-cost drone technology combined with deep learning capabilities on consumer hardware offers new avenues for monitoring forest health and canopy structure changes [2].

Additionally, machine learning techniques applied to diverse datasets enhance assessments of forest health, species distribution, and biomass estimation, underscoring the transformative potential of remote sensing technologies [12]. Tools like Sen2Chain, an open-source Python toolbox for processing Sentinel-2 image time series, further exemplify advancements in environmental health and ecology applications [13].

However, the limitations of optical data sources under adverse weather conditions necessitate the integration of synthetic aperture radar (SAR) data, which is less affected by such constraints and

provides valuable insights for forest classification [14]. Effective monitoring and mitigation strategies are critical for biodiversity protection and climate change response, with citizen science initiatives significantly contributing by engaging volunteers in identifying deforested areas.

1.3 Structure of the Survey

This survey provides a comprehensive analysis of tropical forest degradation, emphasizing the vital role of remote sensing technologies, particularly LiDAR and advanced superpixel segmentation methods, in monitoring and managing these ecosystems [1, 9]. The introduction outlines the significance of tropical forest degradation and the critical contributions of remote sensing technologies in understanding these changes. Following this, the survey presents background information and core concepts, including canopy structure, tree architecture, and spatiotemporal dynamics.

Subsequent sections focus on remote sensing technologies, discussing various tools and methods such as LiDAR, high-resolution imagery, UAVs, and data fusion techniques essential for forest monitoring. The survey then explores the applications of these technologies in monitoring forest fragmentation, ecological succession, and the impacts of deforestation.

Later sections analyze the spatiotemporal dynamics of forest ecosystems, detailing technological advances and challenges in monitoring these dynamics. Case studies and practical implementations illustrate real-world applications of remote sensing in tropical forest monitoring.

The survey concludes by addressing challenges and future directions in remote sensing technologies, including data accuracy, technological limitations, and potential advancements. This structured approach facilitates a thorough exploration of the complex factors contributing to tropical forest degradation while highlighting the advanced capabilities of remote sensing technologies, such as LiDAR and superpixel segmentation methods, in effectively addressing these challenges [1, 9]. The following sections are organized as shown in Figure 1.

2 Background and Core Concepts

2.1 Tropical Forest Degradation

Tropical forest degradation, driven by anthropogenic and natural factors, results in deforestation, biodiversity loss, and reduced ecosystem services such as carbon sequestration [2]. Effective management requires accurate mapping of indigenous and plantation forests, though traditional methods often struggle with complex canopy structures [4, 15]. Changes in land use and cover significantly impact environmental data analysis and agricultural practices [16]. Edge effects and fire dynamics are critical in shaping forest communities and maintaining ecological stability. Accurate estimation of aboveground carbon density (ACD) is crucial, as demonstrated by Airborne Laser Scanning (ALS) studies in Borneo [3].

Technologies like UAV-based imagery and Canopy Height Models (CHMs) provide high-resolution data essential for assessing forest health and dynamics [17]. These tools enable precise mapping of canopy height and crown area, crucial for monitoring degradation [18]. The integration of data-driven methodologies and open data initiatives enhances the accessibility and utility of remote sensing data, promoting comprehensive monitoring and management of tropical forests [12].

2.2 Canopy Structure and Tree Architecture

Canopy structure and tree architecture are pivotal for forest ecosystem functioning, affecting light penetration, microclimate, and habitat availability, which in turn influence biodiversity and ecosystem dynamics [19]. Mapping canopy height is especially critical in primeval forests for conserving biodiversity and ecosystem services [20]. Segmenting individual trees in complex forests is challenging due to overlapping foliage [19], yet essential for assessing forest health and resilience.

Remote sensing technologies like LiDAR and high-resolution imagery have transformed canopy structure studies, providing accurate measurements of tree height, crown dimensions, and spatial distribution. Advanced segmentation methods, using vertical stratification, improve tree identification accuracy, especially for understory trees, while integrating 3D LiDAR with hyperspectral imagery

refines crown assessments [21, 19, 17, 18, 22]. High-resolution canopy height maps are crucial for understanding carbon dynamics and sustainable land-use practices [23, 24, 22].

2.3 Spatiotemporal Dynamics

Understanding spatiotemporal dynamics is vital for elucidating interactions within forest ecosystems, especially concerning tropical forest degradation. Forest landscape dynamics involve significant shifts in spatial patterns and temporal sequences, crucial for evaluating fragmentation and its ecological impacts. Factors such as edge effects, fire propagation, and tree population dynamics influence forest patch stability and distribution. High-resolution remote sensing and advanced modeling, including dynamic spatial regression models, enhance assessments of these dynamics for improved management strategies [25, 7, 26, 27, 6].

Integrating remote sensing with spatiotemporal analysis has improved monitoring capabilities, with spatiotemporal fusion enhancing resolution for effective time-series analysis [28]. These approaches capture subtle forest changes often missed by traditional methods. Innovative analytical approaches are needed to quantify movement patterns across spatial and temporal scales [27], crucial for identifying fragmentation drivers and assessing biodiversity impacts. This knowledge aids in predicting forest change trajectories and developing targeted conservation strategies.

Investigating spatiotemporal dynamics reveals interactions among factors like fire dynamics and deforestation patterns, essential for informed management strategies to address deforestation and ecosystem instability. Advanced methodologies, including high-resolution remote sensing and dynamic spatial regression models, enable comprehensive assessments of forest stability and inform targeted interventions [25, 1, 6, 29].

2.4 Importance of Accurate Biomass and Carbon Estimation

Accurate biomass and carbon stock estimation is crucial for effective forest monitoring, providing insights into carbon dynamics and informing climate change mitigation strategies. High-resolution canopy height maps are instrumental for precise biomass estimation over large areas, aiding in assessments of forest degradation and restoration [30]. Integrating advanced remote sensing technologies like LiDAR and UAVs captures spatial variability in forest ecosystems, improving biomass assessment accuracy [5].

Estimating vegetation strata occupancy from airborne 3D LiDAR data is vital for detailed biomass analysis, providing insights into vertical distribution [31]. Reliable remote sensing maps are necessary for evaluating forest inventory model transferability, underscoring the importance of precise biomass and carbon stock estimation [32]. Benchmarks for tree crown delineation algorithms highlight the need for quantitative metrics accommodating annotation imprecision, enhancing biomass estimation accuracy [15].

Multimodal remote sensing data, including hyperspectral, multispectral, and SAR, offers a comprehensive approach to land cover classification and biomass estimation, improving integration and classification of diverse forest types [33]. Challenges remain in achieving accurate segmentation and detection due to intricate forest details and the need for large labeled datasets for deep learning models [34]. Accurate Leaf Area Index (LAI) estimation is also critical for understanding ecosystem health, as shown by multi-temporal Sentinel-1 data [35].

Dynamic spatial regression models emphasize the necessity for precise stand table estimates, crucial for sustainable forest management and accurate biomass and carbon estimations [25]. Object-based spatial unmixing methodologies enhance time-series observation accuracy, facilitating refined biomass change analyses [28].

3 Remote Sensing Technologies

The exploration of remote sensing technologies in forest monitoring reveals a spectrum of methodologies that have significantly advanced the field. Table 1 presents a comprehensive summary of the methodologies employed in remote sensing technologies for forest monitoring, showcasing the integration of LiDAR, high-resolution imagery, UAVs, advanced data fusion, and machine learning applications. Additionally, Table 5 offers a detailed comparison of remote sensing technologies,

Category	Feature	Method
LiDAR Technology	Data Fusion and Integration Biomass and Carbon Estimation	IMLA[36] RALCD[3]
High-Resolution Imagery and Photogrammetry	Data Integration Techniques	PRFX[20], RTSM[19], HLI-FM[5]
UAVs and Drone Technologies	UAV Monitoring Technologies	TB[37], PPN[38], RID[39], DL-SEG[2], ATCS[40]
Advanced Data Fusion and Image Analysis	Data Integration Techniques Probabilistic Analysis Methods	UAS-DAP-LiDAR[41], OBSUM[28], SAAI[42], MVSM[43], MCRC[17] SMM[44]
Machine Learning and Deep Learning Applications	Data Integration Techniques	MLCM[45], LAI-DL[35]

Table 1: Summary of Methods Applied in Remote Sensing Technologies for Forest Monitoring. This table categorizes various methodologies across different remote sensing technologies, including LiDAR, high-resolution imagery, UAVs, advanced data fusion, and machine learning applications. Each category highlights specific features and the corresponding methods employed, demonstrating the diverse approaches utilized to enhance environmental monitoring and analysis.

illustrating their respective data types, primary applications, and integration techniques in the context of forest monitoring. This section delves into pivotal techniques, beginning with LiDAR technology, which has revolutionized forest ecosystem analysis by offering high-resolution, three-dimensional data essential for detailed assessments of canopy structure and tree architecture. ?? illustrates the hierarchical structure of remote sensing technologies applied in forest monitoring, highlighting not only LiDAR technology but also high-resolution imagery and photogrammetry, UAVs and drone technologies, advanced data fusion and image analysis, as well as machine learning and deep learning applications. Each of these categories is further broken down into specific applications, integration techniques, and innovative uses, thereby showcasing the comprehensive advancements in remote sensing methodologies that facilitate effective environmental monitoring and analysis.

3.1 LiDAR Technology

LiDAR (Light Detection and Ranging) is a groundbreaking tool in forest studies, providing high-resolution, 3D data crucial for analyzing canopy structure and tree architecture. It captures precise elevation and size information, facilitating detailed assessments of forest canopies and revealing vegetation's spatial distribution and vertical stratification [19]. The synergy of LiDAR with hyperspectral data enhances classification accuracy in complex environments, offering a comprehensive view of forest ecosystems [5].

As illustrated in Figure 2, which depicts the hierarchical structure of LiDAR technology applications in forest studies, key areas such as applications, data integration, and technological advancements are highlighted. This visual representation emphasizes the synergy of LiDAR with other technologies, its diverse applications in forest research, and recent innovations that enhance its capabilities.

LiDAR's primary applications include creating advanced canopy height models, such as the Global Canopy Height Model (GCHM), which integrates GEDI LiDAR data and Sentinel-2 imagery to refine canopy height estimates [20]. Techniques like Vertical Stratification of Forest Canopy (VSFC) improve understory tree detection and tree crown segmentation [19].

In biomass estimation, LiDAR is pivotal. Combining Airborne, Terrestrial, and Mobile Laser Scanning platforms significantly enhances biomass assessment accuracy [36]. The LiDAR-Forest benchmark evaluates algorithms for forest reconstruction, tree diameter estimation, and point cloud visualization, highlighting LiDAR's importance in forest monitoring [46]. Deep learning models like PRFXception, which map forest canopy heights by fusing spaceborne LiDAR and optical imagery, illustrate LiDAR's capability in assessing the vertical distribution of forest components [20].

LiDAR also aids in analyzing edge effects, categorizing research by edge types and their ecological implications [26]. Integrating Airborne Laser Scanning with field measurements, such as basal area and wood density, helps estimate aboveground carbon density in tropical forests, underscoring LiDAR's critical role in biomass and carbon stock assessments [3].

3.2 High-Resolution Imagery and Photogrammetry

High-resolution imagery and photogrammetry are crucial for advancing forest monitoring, providing detailed visual and spatial data that enhance understanding of forest ecosystems. These technologies

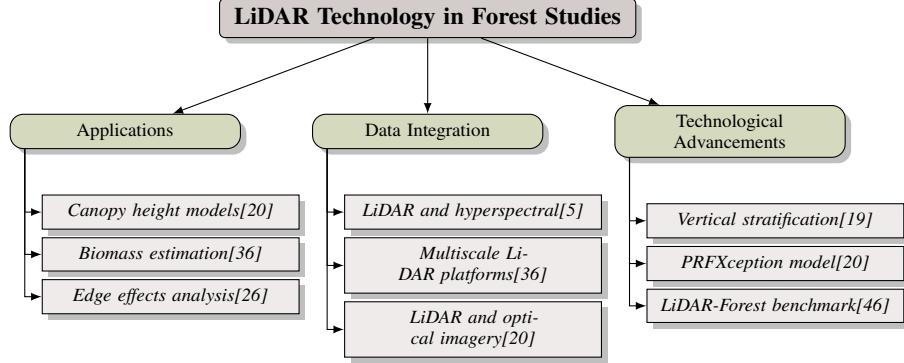


Figure 2: This figure illustrates the hierarchical structure of LiDAR technology applications in forest studies, highlighting key areas such as applications, data integration, and technological advancements. It emphasizes the synergy of LiDAR with other technologies, its use in various forest applications, and recent technological innovations.

Method Name	Technological Integration	Application Scope	Methodological Advancements
PRFX[20]	Remote Sensing Technologies	Mapping Forest Structures	Machine Learning Techniques
RTSM[19]	Lidar Technology	Forest Structures Mapping	Distributed Computing Strategy
HLI-FM[5]	Lidar Hyperspectral Data	Forest Management	Machine Learning Classifiers
OBSUM[28]	Remote Sensing Technologies	Crop Monitoring	Machine Learning Techniques

Table 2: Overview of methodologies integrating remote sensing technologies for forest monitoring, highlighting technological integration, application scope, and methodological advancements. Each method utilizes advanced techniques such as machine learning and distributed computing to enhance forest structure mapping and management.

enable precise mapping of forest structures, facilitating assessments of canopy cover, tree height, and species composition. The integration of high-resolution optical imagery with advanced photogrammetric techniques generates detailed digital elevation models (DEMs) and orthophotos, vital for analyzing forest dynamics and detecting temporal changes [20]. Table 2 presents a comprehensive analysis of various methodologies employing remote sensing technologies for forest monitoring, emphasizing their technological integration, application scope, and methodological advancements.

Photogrammetry, especially with UAV platforms, offers a cost-effective, flexible method for acquiring high-resolution data across large areas, crucial for monitoring remote or inaccessible forests [19]. Structure-from-Motion (SfM) photogrammetry reconstructs 3D forest structures from overlapping 2D images, providing insights into canopy architecture and tree density [5].

Automated image processing algorithms enhance high-resolution imagery applications by facilitating forest parameter extraction, improving forest inventory accuracy. These advancements enable efficient land cover classification, detection of deforestation and degradation patterns, and monitoring of forest health and biodiversity [33]. Integrating high-resolution imagery with other remote sensing data, like LiDAR and multispectral imagery, enhances comprehensive forest assessments and robust management strategies [20].

The synergy between high-resolution imagery and machine learning techniques revolutionizes forest data analysis, enabling automatic tree species identification and biomass and carbon stock estimation. This integration supports creating detailed forest maps crucial for conservation planning and climate change mitigation efforts [34]. Innovative methodologies, such as object-based image analysis (OBIA), allow precise delineation of forest features and spatial pattern assessment, deepening understanding of forest ecosystem dynamics [28].

3.3 UAVs and Drone Technologies

Unmanned Aerial Vehicles (UAVs) and drone technologies are vital in remote sensing, offering enhanced flexibility and precision in environmental monitoring and forest management. Equipped with advanced sensors, these platforms facilitate comprehensive data collection, making them indispensable for forest monitoring, wildlife detection, and tree classification [47]. Integrating UAVs

Method Name	Technological Integration	Analytical Techniques	Application Domains
ATCS[40]	Uav Photography	Deep Learning	Forest Management
DL-SEG[2]	Rgb Aerial Data	Deep Learning	Forest Monitoring
RID[39]	Advanced Sensors	Deep Learning	Forest Management
SAAI[42]	Dji Enterprise Drones	Anomaly Detection	Environmental Monitoring
TB[37]	Advanced Sensors	Metric Learning Methods	Forest Management
PPN[38]	Uav Technology	Deep Learning	Environmental Monitoring

Table 3: Overview of UAV and drone technology applications in environmental monitoring and forest management, highlighting the integration of technological methods, analytical techniques, and application domains. Each method utilizes UAV platforms with advanced sensors and deep learning algorithms to enhance data collection and analysis in diverse ecological contexts.

with RGB imaging provides a cost-effective solution for tree classification, significantly aiding forest management efforts [40].

Table 3 presents a comprehensive summary of various UAV and drone technology applications, detailing their technological integration, analytical techniques, and specific application domains within environmental monitoring and forest management. UAV applications are further augmented by deep learning techniques that process high-resolution imagery to detect specific forest attributes, such as fallen trees and tree crown dieback. UAV imagery combined with deep learning algorithms effectively identifies degraded Acacia trees, surpassing traditional satellite imagery methods in accuracy [48]. Additionally, segmenting individual tree crowns from RGB aerial imagery using vegetation indices allows for assessing crown dieback, providing critical data for evaluating forest health [2].

In forest fire monitoring, drones provide timely data essential for effective fire control and disaster management strategies [39]. Technologies like Synthetic Aperture Anomaly Imaging (SAAI) enhance UAV capabilities in detecting targets obscured by foliage, highlighting their potential for anomaly detection and environmental surveillance [42].

UAVs also verify forest conservation projects. Techniques like TrueBranch employ metric learning-based verification to compare drone imagery with public satellite data, ensuring information reliability in conservation efforts [37]. In agriculture, probabilistic models like PalmProbNet use transfer learning to process UAV-derived orthomosaic imagery for palm tree detection, showcasing UAVs' versatility in ecological and agricultural contexts [38].

UAVs and drone technologies represent significant advancements in remote sensing applications, providing high-resolution data and innovative analytical capabilities that enhance understanding of forest ecosystems. These technologies contribute to effective environmental management and conservation strategies, underscoring their critical role in modern remote sensing efforts [34].

3.4 Advanced Data Fusion and Image Analysis

Method Name	Data Integration	Algorithmic Innovation	Analytical Techniques
UAS-DAP-LiDAR[41]	Digital Aerial Photogrammetry	-	Predictive Models
MVSM[43]	Semantic Meshes	3D Mesh Representation	Deep Learning Predictions
MCRC[17]	Lidar Point Cloud	Graph Cut Approach	Graph Cut Segmentation
OBSUM[28]	Remote Sensing Images	Object-based Image Analysis	Object-level Unmixing
SMM[44]	Gedi Lidar Measurements	Mixture Model	Gaussian Processes
SAAI[42]	Thermal Images	Anomaly Detection	Target Detection

Table 4: Overview of advanced data fusion and image analysis methods utilized in remote sensing technologies for forest monitoring, highlighting the integration of various data types, algorithmic innovations, and analytical techniques. These methods underscore the potential for improved accuracy and reliability in forest ecosystem assessments through the combination of diverse data perspectives and cutting-edge algorithms.

Advanced data fusion and image analysis techniques are integral to enhancing remote sensing technologies in forest monitoring, enabling more precise and comprehensive assessments of forest ecosystems. By integrating multiple data sources, such as UAS-based digital aerial photogrammetry and LiDAR, researchers can generate high-resolution canopy height models crucial for accurate biomass estimation [41]. This fusion approach capitalizes on each data type's strengths, leading to

improved accuracy and reliability in forest assessments. Table 4 presents a comprehensive overview of advanced data fusion and image analysis methodologies employed in remote sensing, detailing the integration of diverse data sources, innovative algorithms, and analytical techniques pivotal for enhancing forest monitoring accuracy and effectiveness.

Novel methodologies in image fusion have propelled the field forward. For instance, the MVSM method leverages deep learning predictions from multiple viewpoints to create a coherent geospatial representation, significantly enhancing species classification accuracy from 53% to 75% [43]. This demonstrates the potential of integrating diverse data perspectives to improve classification outcomes.

Innovative algorithms, such as the graph cut approach, combine graph cut segmentation with rich data from LiDAR and hyperspectral imagery. This integration allows for more accurate delineation of individual trees compared to traditional Canopy Height Model (CHM)-based methods, highlighting the value of combining different data modalities for enhanced analysis [17].

The OBSUM methodology represents a significant advancement in data fusion techniques by integrating object-based image analysis with spatial unmixing, facilitating detailed and accurate analysis of forest structures and dynamics [28]. Additionally, applying Gaussian processes in spatial mixture models offers a probabilistic framework for classifying observations, enhancing land cover classification precision and forest monitoring [44].

The use of Synthetic Aperture Anomaly Imaging (SAAI) exemplifies advancements in image analysis by integrating detected anomalies from individual thermal images, improving target detection in occluded environments, particularly valuable in challenging forest settings where visibility is limited [42].

Advancements in data fusion and image analysis are pivotal in enhancing remote sensing technologies for forest monitoring. Integrating diverse data sources and employing cutting-edge analytical techniques like machine learning and deep learning, researchers achieve more accurate and comprehensive assessments of forest ecosystems. This approach not only improves carbon stock estimations and tree species identification but also facilitates monitoring of deforestation and ecosystem health, contributing to effective conservation and management strategies in the face of climate change and human impacts [7, 12, 23, 49, 37].

3.5 Machine Learning and Deep Learning Applications

The integration of machine learning and deep learning techniques in remote sensing data analysis has significantly advanced forest monitoring capabilities, enabling more precise and efficient environmental assessments. These computational methodologies extract complex patterns from large datasets, enhancing decision-making in conservation efforts. For instance, deep neural networks using multiple U-nets have been proposed to predict Leaf Area Index (LAI) by processing Sentinel 1 radar and Sentinel 2 multispectral data, demonstrating deep learning's potential in vegetation monitoring [35].

A critical challenge in deploying deep learning models for real-time applications in remote sensing is the trade-off between effectiveness and efficiency. While many efficient deep neural networks (DNNs) excel in segmentation quality, they often suffer from low inference speed and high latency rates, limiting their applicability in real-time scenarios [50]. This highlights the need for DNN methods that balance segmentation performance with computational efficiency for real-time semantic segmentation in remote sensing imagery.

Deep learning applications extend to various aspects of remote sensing, including land cover classification and change detection. Specialized models employing transfer learning enhance feature extraction and classification accuracy, underscoring machine learning's transformative role in spatial data analysis. The use of deep convolutional neural networks (CNNs) for estimating canopy height from multispectral images represents a significant advancement in integrating machine learning within remote sensing technologies. This approach enables precise vegetation height measurements, essential for understanding ecosystem dynamics and enhancing forest management strategies by facilitating informed conservation and sustainable land use practices. Moreover, advanced models leveraging multi-temporal satellite data and self-supervised learning techniques underscore the potential for improved accuracy and efficiency in canopy height mapping, contributing to effective monitoring of forest health and carbon dynamics [14, 51, 18, 35, 40].

The integration of machine learning and deep learning into remote sensing data analysis marks a transformative leap in forest monitoring technologies, enabling cost-effective and highly accurate classification of tree species through innovative methods, such as using UAVs and object-based deep learning techniques, which classify multiple tree types with impressive precision using standard RGB images. This advancement enhances the capabilities of forest researchers and land managers while addressing significant environmental challenges like climate change and urbanization through data-intensive scientific approaches [40, 8]. These methodologies improve environmental assessment accuracy and contribute to more effective conservation and management strategies, underscoring their critical role in modern remote sensing applications.

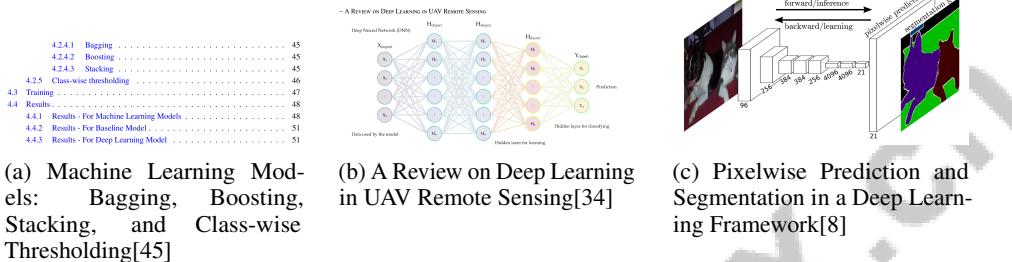


Figure 3: Examples of Machine Learning and Deep Learning Applications

As shown in Figure 3, the integration of machine learning and deep learning applications in remote sensing technologies is increasingly pivotal. The first example highlights machine learning models like Bagging, Boosting, Stacking, and Class-wise Thresholding, which are crucial for enhancing remote sensing data classification accuracy and efficiency. The second illustration delves into the architecture of deep neural networks (DNNs) employed in UAV remote sensing, showcasing sophisticated layers that process sensor data to derive meaningful insights. Lastly, the third example presents a deep learning framework for pixelwise prediction and segmentation, emphasizing the intricate forward and backward processes underpinning its functionality. Together, these examples underscore the transformative impact of machine learning and deep learning in advancing remote sensing technologies, facilitating more precise and comprehensive environmental monitoring and analysis [45, 34, 8].

Feature	LiDAR Technology	High-Resolution Imagery and Photogrammetry	UAVs and Drone Technologies
Data Type	3D Data	Visual Data	Aerial Imagery
Primary Application	Canopy Analysis	Forest Mapping	Wildlife Detection
Integration Technique	Hyperspectral Synergy	Photogrammetric Techniques	Deep Learning

Table 5: This table provides a comparative analysis of various remote sensing technologies utilized in forest monitoring. It highlights the data types, primary applications, and integration techniques associated with LiDAR technology, high-resolution imagery and photogrammetry, and UAVs and drone technologies. The comparison underscores the diverse methodologies and technological synergies that enhance environmental monitoring and analysis.

4 Applications in Forest Monitoring

A nuanced understanding of remote sensing technologies is vital for effective forest monitoring, particularly in evaluating forest fragmentation. This section examines methodologies that provide critical insights into the structural and ecological dynamics of forest ecosystems, aiding in the assessment of fragmentation impacts and the development of strategies to enhance forest resilience and sustainability.

4.1 Remote Sensing Techniques for Forest Fragmentation Monitoring

Remote sensing techniques are pivotal in monitoring forest fragmentation, offering detailed insights into the spatial and temporal dynamics of forest ecosystems. Technologies like LiDAR, UAVs, and advanced data fusion significantly enhance the precision of forest structure assessments and

fragmentation analysis. LiDAR is instrumental in evaluating edge dynamics in fragmented landscapes, such as Eucalyptus plantations, where it helps mitigate edge effects [26]. By enabling vertical stratification of forest canopies, LiDAR aids in detecting understory trees, providing a comprehensive view of forest composition and fragmentation [31].

UAVs, equipped with advanced sensors, acquire high-resolution data essential for identifying structural and compositional changes over time. The integration of UAVs with deep learning techniques improves tree species classification accuracy, exemplified by methods like PalmProbNet, which generates probability heatmaps for palm presence [38]. Advanced data fusion approaches, such as multiview reasoning, enhance biomass estimates and facilitate cost-effective assessments of forest fragmentation [43]. The CNN-VHM method allows for high-resolution vegetation height mapping, critical for understanding fragmentation's ecological impacts [30].

Innovative algorithms for generating mid-story fuel layouts demonstrate the effectiveness of remote sensing in capturing diverse landscape characteristics and improving understanding of fragmentation's ecological impacts. Advanced image analysis methods, such as those estimating tree crown dieback, further enhance monitoring capabilities [2]. These technologies provide essential tools for assessing the spatial and ecological impacts of forest fragmentation with greater precision, promoting sustainable forest management practices and biodiversity conservation [1, 7, 12, 23, 49].

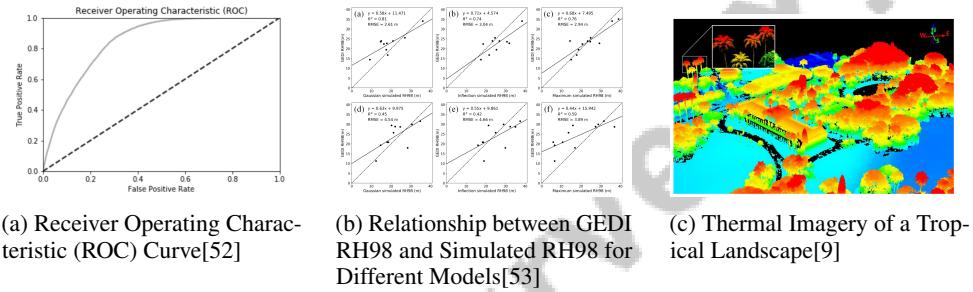


Figure 4: Examples of Remote Sensing Techniques for Forest Fragmentation Monitoring

As illustrated in Figure 4, remote sensing techniques are instrumental in assessing and managing forest fragmentation. The ROC curve evaluates the performance of binary classifiers crucial for detecting changes in forest cover. The relationship between GEDI RH98 and simulated RH98 values across different models provides a comparative analysis of model accuracy in representing forest canopy structure. Additionally, thermal imagery vividly depicts temperature variations in tropical landscapes, crucial for identifying areas of deforestation or habitat change. Collectively, these techniques highlight the diverse applications of remote sensing in monitoring and preserving forest health and biodiversity [52, 53, 9].

4.2 Ecological Succession and Biodiversity Assessment

Remote sensing technologies have revolutionized the assessment of ecological succession and biodiversity in forest ecosystems, providing comprehensive data that enhance our understanding of these complex processes. Monitoring changes in vegetation structure and composition over time is crucial for evaluating ecological succession stages, directly informing biodiversity conservation strategies. Advanced methodologies, including non-destructive carbon estimation techniques and deep learning-based monitoring tools, enable accurate tracking of forest health and ecosystem services, facilitating informed conservation efforts and improving ecosystem service payment programs [7, 2, 23, 26, 37]. High-resolution remote sensing imagery from UAVs and satellite platforms facilitates detailed mapping of successional stages, enabling tracking of forest recovery following disturbances like deforestation or fire.

Integrating LiDAR technology with hyperspectral and multispectral imagery allows for precise characterization of canopy structure and species composition, essential for understanding biodiversity patterns. LiDAR captures three-dimensional forest structure, providing insights into habitat complexity and resource availability, critical factors influencing species distribution and diversity [5]. Furthermore, advanced image fusion techniques, such as those used in the MVSM method, enhance species classification accuracy, improving biodiversity assessments [43].

Machine learning and deep learning applications augment remote sensing capabilities in biodiversity assessment by automating species identification and estimating biodiversity indices. These computational approaches facilitate analysis of large datasets, enabling efficient detection of biodiversity hotspots and monitoring changes in species richness over time. Probabilistic models like PalmProb-Net exemplify the potential of remote sensing technologies to enhance understanding of species distribution and ecological succession [38].

Remote sensing technologies offer invaluable tools for assessing ecological succession and biodiversity, providing detailed insights into the dynamic processes shaping forest ecosystems. Utilizing advanced imaging techniques such as drone-based thermal imaging and superpixel segmentation methods, alongside sophisticated analytical methodologies, researchers can gain deeper insights into species-environment interactions. This understanding is crucial for developing targeted conservation and management strategies, particularly in the face of challenges like deforestation and wildlife monitoring. Citizen science initiatives can leverage improved segmentation techniques for identifying deforested areas, while automated wildlife detection can streamline data collection across larger landscapes, contributing to more effective conservation efforts [54, 7, 10, 27].

4.3 Deforestation Impact Analysis

Remote sensing technologies have become indispensable for analyzing deforestation impacts, providing crucial data that inform conservation strategies and climate mitigation efforts. The integration of advanced methodologies like LiDAR and hyperspectral data has significantly improved classification accuracy with limited training samples, underscoring their potential in forest monitoring applications [4]. Regional models estimating aboveground carbon density (ACD) from Airborne Laser Scanning (ALS) data represent a significant advancement in accurately mapping forest carbon stocks, as evidenced by studies in Borneo [3].

Machine learning approaches, including Temporal Convolutional Neural Networks (TempCNNs), have enhanced land cover mapping accuracy, surpassing traditional methods such as Random Forests and Recurrent Neural Networks [55]. These advancements facilitate the detection of deforestation patterns and contribute to a comprehensive understanding of land cover changes. The challenge of detecting deforestation in cloud-covered regions like the Amazon can be addressed by combining recurrent and residual learning techniques to improve detection accuracy [29].

Bayesian change point models have proven highly accurate in detecting land cover changes in MODIS time series data, providing valuable insights into these changes and significantly contributing to remote sensing applications [56]. Additionally, graph-based fusion methods for change detection have outperformed traditional probabilistic threshold methods, establishing themselves as promising approaches for remote sensing applications [57].

The integrity of Payments for Ecosystem Services (PES), critical for accurate deforestation impact analysis, can be compromised by landowners' potential misreporting of drone imagery [37]. Ensuring the reliability of remote sensing data is therefore paramount for effective deforestation monitoring and analysis. Evaluating superpixel methods has revealed that improved delineation and color homogeneity lead to better classification outcomes, further enhancing deforestation impact assessments [1].

Remote sensing technologies provide indispensable tools for analyzing deforestation impacts, offering detailed and accurate data that support effective conservation and climate mitigation strategies. By leveraging advanced methodologies such as deep learning and high-quality remote sensing technologies, alongside comprehensive datasets like ReforestTree and OpenForest, researchers can gain deeper insights into deforestation dynamics. This understanding enables the development of targeted interventions that preserve forest ecosystems and improve carbon stock assessment accuracy and accountability, ultimately supporting scalable financing initiatives for reforestation and sustainable forest management [49, 6, 12].

4.4 Innovations in Forest Health and Conservation Monitoring

Innovative approaches to monitoring forest health and conservation efforts have been significantly enhanced by integrating advanced remote sensing technologies and data analysis methodologies. The combination of LiDAR and hyperspectral imaging has markedly improved the accuracy of forest

inventory assessments, showcasing the potential of these technologies in advancing forest monitoring and conservation strategies [21]. These advancements enable the automatic extraction of high-level features from complex datasets, leading to improved classification and analysis accuracy [8].

Deep learning methods have revolutionized remote sensing tasks by automating labor-intensive processes, enhancing accuracy and efficiency in forest monitoring [34]. User-friendly tools like Sen2Chain facilitate efficient processing of large datasets, contributing to innovative environmental health monitoring and natural hazard assessment strategies [13].

Moreover, UAVs have become critical for enhancing environmental monitoring, with ongoing research focusing on sensor integration and standardization of data analysis methodologies [47]. These technologies provide comprehensive data collection capabilities, allowing for more efficient responses to forest health challenges and conservation needs. The synthesis of high-quality synthetic images conditioned on phenotypic attributes offers a novel approach to forest monitoring, enabling the generation of biologically plausible data for modeling various environmental scenarios [58].

The integration of remote sensing data to model disturbance impacts and explore interactions among environmental factors, such as fire and wind, on forest structure is essential for developing evidence-based restoration strategies [11]. Proposed methods for predicting forest naturalness provide an interpretable framework that assists stakeholders in making informed decisions regarding forest management and conservation [59].

In forest fire prevention, innovative approaches have been developed to optimize data collection and response efficiency during fire incidents, enabling the handling of more tasks within the same timeframe [39]. These advancements underscore the importance of leveraging technology to enhance forest health monitoring and conservation efforts, ultimately contributing to the sustainable management of forest ecosystems.

5 Spatiotemporal Dynamics and Forest Fragmentation

5.1 Forest Fragmentation and Ecological Implications

Forest fragmentation significantly alters ecological succession and biodiversity, affecting forest ecosystem structure and function by creating isolated patches that disrupt species distribution and dynamics. Local fire dynamics and edge effects play crucial roles in shaping fragmentation patterns, impacting succession and biodiversity [6]. Edge effects modify microclimatic conditions, influencing species composition and habitat availability.

Challenges in accurately estimating aboveground biomass (AGB), such as signal saturation and inadequate calibration for high AGB values, hinder understanding of fragmentation's ecological impacts [60]. Advanced remote sensing techniques are necessary to improve biomass assessment accuracy, essential for evaluating these impacts.

Innovative models like PalmProbNet achieve high accuracy in species detection, providing insights into fragmentation's ecological implications [38]. Such models enhance understanding of species distribution in fragmented landscapes, aiding conservation strategies.

Advancements in Synthetic Aperture Anomaly Imaging (SAAI) improve occlusion removal and target detection in vegetation-obscured areas, enhancing ecological assessments in fragmented forests [42]. These innovations address monitoring challenges in fragmented ecosystems.

Benchmarks for estimating forest carbon stock in small tropical agroforestry projects help assess carbon dynamics in fragmented landscapes [49]. Accurate carbon stock estimation aids in understanding ecological succession and fragmented forests' role in global carbon cycling.

Advanced remote sensing technologies and analytical methods are vital for effective monitoring and management of fragmented ecosystems. Techniques like superpixel segmentation enhance deforestation area identification, supporting citizen science initiatives for conservation. Airborne LiDAR allows precise segmentation of individual trees in complex canopies, improving understanding of forest structure and health. These advancements are crucial for developing strategies to mitigate fragmentation impacts and enhance ecosystem resilience [7, 19].

5.2 Technological Advances in Monitoring Dynamics

Recent technological advancements have greatly improved the monitoring of spatiotemporal dynamics in forest ecosystems, especially concerning fragmentation. Techniques like iDASF outperform standard methods by reducing estimation bias and providing more accurate Directional Area Scattering Function (DASF) values across various canopy structures [61]. This is crucial for capturing spatiotemporal variations in forest canopies.

Machine learning, particularly Long Short-Term Memory (LSTM)-based approaches, effectively captures temporal dependencies in historical data, offering insights into spatiotemporal dynamics' effects on forest fragmentation [62]. These methodologies enhance prediction and analysis of ecosystem changes over time, supporting conservation strategies.

Lidar-based mapping advancements, such as the SLOAM method, use semantic features to improve mapping accuracy and robustness [63]. These technologies provide detailed assessments of forest structure and dynamics, deepening ecological process understanding.

Iterative, data-driven remote sensing methodologies adapt to forests' structural complexity, addressing segmentation challenges and improving spatiotemporal dynamics monitoring [19]. This adaptability is vital for capturing intricate patterns and dependencies in tree distributions, essential for understanding ecological implications [25].

Recurrent Residual Convolutional Neural Networks (RRCNN) model temporal dependencies in image sequences, enabling subtle change detection indicative of deforestation [29]. This capability is crucial for early deforestation signs identification and timely conservation measures.

Integrating these technological advancements with morphological diversity and carbon storage factors provides a comprehensive framework for understanding spatiotemporal dynamics in forest ecosystems [23]. Leveraging these methodologies enhances forest monitoring accuracy and informs more effective preservation strategies.

5.3 Challenges in Spatiotemporal Analysis

Analyzing spatiotemporal data in forest monitoring is challenging due to the complexity and variability of forest ecosystems. Predicting vegetation stratum occupancy in complex structures is particularly difficult. The developed method for predicting vegetation stratum occupancy may struggle under these conditions, reflecting broader challenges in capturing forest canopy dynamics [64]. Advanced modeling techniques are needed to accommodate spatial and temporal variations in diverse forest environments.

Processing large volumes of spatiotemporal data poses computational challenges. For example, the SRC-Net backbone's computational overhead limits deployment on edge devices [65]. This hinders real-time analysis and decision-making in forest monitoring, highlighting the need for efficient algorithms and hardware solutions for intensive data processing.

Integrating diverse data sources, such as LiDAR, multispectral, and hyperspectral imagery, adds complexity to spatiotemporal analysis. Data fusion techniques that seamlessly combine varied datasets are essential for comprehensive and accurate forest monitoring. Environmental monitoring methodologies face technical challenges, particularly ensuring data compatibility across diverse sources and high accuracy in thermal infrared data analysis, influenced by factors like ambient heat, atmospheric absorption, and vegetation interference. Advanced techniques, including deep learning and image fusion strategies, are necessary to effectively process and analyze data at varying scales and resolutions, enhancing automated conservation efforts and citizen science initiatives' reliability in tracking endangered species and detecting deforestation [8, 66, 7, 10].

6 Case Studies and Practical Implementations

6.1 UAS and LiDAR Applications in Biomass Estimation

Unmanned Aerial Systems (UAS) and Light Detection and Ranging (LiDAR) technologies are crucial for precise biomass estimation in forest management, offering enhanced insights into forest dynamics through high-resolution spatial data acquisition [5]. Their efficacy is demonstrated in Hong Kong's

subtropical rainforests, where they facilitate detailed assessments of forest structure and biomass, supporting effective restoration strategies [11]. The integration of hyperspectral and multispectral imagery with Synthetic Aperture Radar (SAR) data and digital surface models enriches the capability to capture diverse land cover features essential for comprehensive biomass estimation [33].

These technologies have proven effective across various forest types. Experiments using satellite remote sensing and land use and land cover (LULC) classification highlight their reliability, with methods like the Multi-Resolution Contextual Classification (MCRC) validated on datasets from the NewFor benchmark and diverse forest sites in the Alps and the UK [16, 17]. The synergistic use of UAS and LiDAR not only enhances biomass assessment accuracy but also supports sustainable forest management by enabling effective monitoring of forest structure and function. This combined approach aids in developing predictive models for large-scale aboveground biomass (AGB) mapping, crucial for understanding ecological dynamics and informing resource management strategies [22, 67, 19, 41].

6.2 Remote Sensing in Forest Fire Prediction

Remote sensing technologies are pivotal in predicting and managing forest fires, providing insights that enhance prevention strategies and response planning. The integration of satellite imagery and UAV data acquisition offers comprehensive spatial coverage for early detection of fire-prone areas and assessment of fire dynamics [39]. Advanced methodologies, such as Synthetic Aperture Anomaly Imaging (SAAI), improve target detection in occluded environments, especially in dense forests where visibility is limited [42].

UAVs equipped with thermal and multispectral sensors enable real-time monitoring of fire conditions, providing crucial data that inform decision-making during fire events. Rapid deployment of UAVs enhances the efficiency of fire response efforts, aiding in the identification of fire fronts and assessment of fire spread dynamics [34]. Incorporating machine learning algorithms into fire prediction models enhances accuracy by analyzing historical fire data and environmental variables, allowing for proactive fire management strategies that minimize risks and improve response times [6, 52, 39, 68].

In regions like Southeast Asia, where climate change and deforestation have increased fire incidents, remote sensing technologies provide high-resolution and timely data that enhance fire management strategies. Novel approaches utilizing remote sensing data have significantly improved prediction accuracy, achieving over 0.81 area under the receiver operating characteristic curve, compared to conventional methods often below 0.70. Advancements in drone surveillance and generative modeling further optimize fire monitoring and prevention efforts, underscoring the critical role of remote sensing in mitigating the impacts of forest fires on health, social structures, and economies [11, 32, 39, 52, 68].

6.3 Innovative Approaches in Forest Classification

Innovative approaches in forest classification have significantly enhanced the precision and efficiency of forest monitoring. The integration of advanced remote sensing technologies, such as LiDAR, hyperspectral, and multispectral imagery, has improved the ability to classify diverse forest types and conditions by enabling the extraction of high-resolution spatial data crucial for distinguishing between species and forest structures [5].

The advent of machine learning and deep learning techniques has revolutionized forest classification through automated analysis of complex datasets. For instance, convolutional neural networks (CNNs) have shown substantial improvements in land cover classification and vegetation mapping, demonstrating the potential of deep learning in remote sensing applications [34]. These models efficiently process large volumes of data, facilitating the identification of forest attributes and detection of changes over time.

Probabilistic models, such as PalmProbNet, exemplify innovative methodologies in forest classification by utilizing transfer learning to generate probability heatmaps indicating the presence of specific tree species with high accuracy [38]. Data fusion techniques further enhance classification by combining information from multiple remote sensing sources, providing a comprehensive view of forest conditions and enabling more accurate results [28].

These advancements are critical for improving forest monitoring and management, as they allow for accurate carbon stock estimation in tropical forests without destructive sampling. The implementation of automated monitoring, reporting, and verification (MRV) systems, such as the TrueBranch algorithm, ensures the integrity of data collected through drone imagery. These innovations not only enhance the reliability of ecosystem service assessments, such as carbon storage, but also contribute to developing effective conservation and resource management strategies addressing climate change and deforestation challenges [23, 37].

7 Challenges and Future Directions

Remote sensing applications in forest monitoring are confronted with challenges related to data accuracy, technological constraints, and environmental influences. Addressing these challenges requires understanding the factors affecting data integrity and methodological robustness, as well as exploring future technological advancements.

7.1 Data Accuracy and Methodological Challenges

The reliability of remote sensing in forest monitoring is significantly impacted by data accuracy and methodological challenges. Integrating diverse data sources like LiDAR and very high-resolution (VHR) RGB imagery can be problematic, as VHR RGB may lack essential spectral information for certain classifications, affecting accuracy across forest types [1]. Low point density in LiDAR datasets further complicates the detection of understory trees [17]. The reliance on specific training locations, often requiring cloud-free conditions, introduces biases that can skew data accuracy [50]. Moreover, noise sensitivity and inaccuracies in change detection maps, influenced by artifacts and parameter initialization, complicate classification efforts [1]. Methodological challenges are exacerbated by the demand for high inference speeds and low computational complexity, often at the expense of segmentation quality [50]. Addressing these challenges requires advanced methodologies and improved data validation processes to enhance the reliability of forest monitoring applications and support effective conservation strategies [1, 7, 9, 32, 19].

7.2 Technological and Computational Limitations

The effectiveness of remote sensing practices in forest monitoring is significantly influenced by technological and computational limitations. Processing large volumes of remote sensing data demands high computational resources, necessitating specialized hardware and software solutions [50]. Integrating datasets like LiDAR and hyperspectral imagery requires advanced data fusion techniques, which can be computationally intensive [28]. Machine learning and deep learning models face constraints due to the need for substantial computational power, particularly during training and inference [50]. Real-time applications, such as forest fire prediction, are limited by algorithm latency and processing speed [39]. Sensor limitations, including spatial and spectral resolution challenges, persist despite technological advancements [60]. Environmental factors, such as cloud cover and atmospheric conditions, complicate data acquisition, highlighting the need for robust preprocessing techniques [29]. Addressing these limitations requires ongoing research and development, integrating advanced machine learning techniques, and exploring innovations in image fusion methods to improve remote sensing applications [66, 7, 8].

7.3 Sensor Limitations and Environmental Factors

Sensor limitations and environmental factors present significant challenges in collecting remote sensing data for forest monitoring. Remote sensing sensors are sensitive to environmental conditions, such as cloud cover and atmospheric interference, which can obscure data acquisition and compromise accuracy. Optical sensors are particularly affected by cloud cover, necessitating alternative data sources like synthetic aperture radar (SAR) [14]. The spatial and spectral resolution of sensors limits their ability to capture detailed forest attributes, creating a trade-off between resolution and coverage that can hinder effective monitoring [20]. Signal saturation in high biomass density regions complicates the accurate estimation of forest parameters [60]. Environmental factors, including topography and vegetation density, further influence sensor performance, requiring multiple sensor modalities for comprehensive data [17]. Integrating multiple data sources and developing robust data

fusion techniques are essential to address these challenges, enhancing accuracy and reliability in forest monitoring [1, 7, 8, 19, 52].

7.4 Integration and Application of Remote Sensing Data

The integration and application of remote sensing data are crucial for advancing forest monitoring, providing insights into forest dynamics and informing conservation strategies. Fusing data sources like optical, LiDAR, and radar imagery enhances the accuracy and reliability of forest assessments by leveraging each modality's strengths [69]. Remote sensing applications include mapping forest cover, assessing biomass and carbon stocks, and detecting structural changes. Integrating high-resolution imagery with LiDAR-derived canopy height models enables detailed mapping of forest attributes [20]. Advanced data fusion techniques, such as object-based spatial unmixing, enhance the capacity to analyze complex ecosystems and detect subtle changes. Incorporating regrowing forest data into analyses provides insights into recovery dynamics, supporting the development of accurate models for predicting forest growth [69]. This multifaceted approach improves carbon stock estimates and enhances understanding of forest composition and climate change impacts, contributing to effective management and preservation of forest ecosystems [49, 23, 12].

7.5 Future Directions and Technological Advancements

The future of remote sensing in forest monitoring is poised for significant advancements through innovative methodologies and new data sources. Enhancing detection accuracy by integrating multiple channels, such as RGB and thermal data in Synthetic Aperture Anomaly Imaging (SAAI), presents a promising avenue [42]. Future research should focus on developing efficient data augmentation techniques and exploring unsupervised learning methods, facilitating the integration of deep learning with traditional remote sensing [8]. Refining LiDAR methodologies and exploring new technologies are essential for addressing data quality challenges [9]. Innovative machine learning strategies that leverage limited labeled data and integrate diverse datasets are crucial for future research [12]. Expanding datasets to encompass diverse ecosystems and improving model generalizability are vital for advancing applications [18]. Future research should also enhance feature extraction techniques, explore additional forest types, and integrate verbal explanation systems to improve stakeholder understanding [59]. Reducing computational requirements and applying modules in multi-temporal change detection tasks are critical for advancing methodologies [65]. Enhancing models like the Joint Gaussian Processes (JGP) for multi-source data scenarios will improve applicability across domains [70]. Exploring robustness against varying land-cover types and extending frameworks for multiview object detection can indicate potential advancements [43]. Integrating contextual information and exploring advanced loss functions can further enhance detection capabilities [71].

8 Conclusion

Remote sensing technologies are instrumental in tackling the challenges of tropical forest degradation. The fusion of hyperspectral and LiDAR data enhances the precision of tree species identification and biomass estimation, forming a robust basis for forest management. Advances in canopy height models, such as the GCHM, refine canopy height measurements and offer uncertainty estimates, thereby improving forest monitoring accuracy. Innovations in 3D deep learning highlight the potential for high precision and efficiency in vegetation analysis. The FOR-instance dataset advances tree segmentation research, promoting methodological development and enabling robust comparisons. Generative modeling techniques offer a versatile approach to characterizing mid-story fuels, which is crucial for wildfire modeling and environmental assessments. Multitemporal SAR images, exemplified by the RRCNN-1 architecture, enhance deforestation detection capabilities. The PlaniSphere framework improves LULC classification accuracy, underscoring the value of spatial data integration in mitigating forest degradation. Furthermore, calibrated regression models demonstrate promise in enhancing above-ground biomass mapping. Insights from models like BGT emphasize the importance of understanding edge effects and fire dynamics for effective forest management. Future research should focus on refining superpixel methods to enhance deforestation detection capabilities.

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