Individual Tree Crown Delineation and Detection in Tropical Forests: A Survey

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Abstract

The survey paper delves into the advancements in individual tree crown delineation and detection within tropical forests, emphasizing the integration of advanced technologies such as LiDAR, UAV remote sensing, and hyperspectral imaging with deep learning techniques. These technologies have revolutionized the precision and efficiency of tree crown mapping, providing critical data for ecological assessments and forest management. The deployment of convolutional neural networks has further enhanced detection accuracy through robust instance segmentation capabilities. The application of these methodologies significantly contributes to biodiversity assessments, carbon stock estimation, and sustainable forest management, demonstrating their transformative impact on ecological monitoring. However, challenges related to data quality, computational complexity, and model generalization persist. Addressing these requires innovation in sensor technologies, data fusion techniques, and adaptive algorithms to improve model robustness and scalability. Future research should focus on expanding dataset sizes, incorporating multi-temporal data, and exploring satellite imagery to enhance detection methodologies. The development of specialized neural network architectures and unsupervised domain adaptation techniques will be crucial for advancing real-time applications and improving model adaptability to diverse environmental conditions. By addressing these research directions, significant advancements in tree crown delineation can be achieved, supporting sustainable forest management and conservation efforts. The integration of these technologies promises to enhance the resilience and sustainability of forest ecosystems, contributing to global biodiversity and climate change mitigation efforts.

1 Introduction

1.1 Significance of Tree Crown Delineation in Tropical Forests

Tree crown delineation in tropical forests is crucial for ecological research and forest management, given these ecosystems' vital roles in global biodiversity and carbon sequestration [1]. The dense and diverse canopies of tropical forests pose unique challenges that require advanced technological interventions for accurate mapping [2]. Such methods facilitate the assessment of forest variables, which are essential for understanding species distribution and ecosystem functions, thereby promoting sustainable management practices [3].

Accurate delineation of tree crowns is fundamental for monitoring forest health, assessing biodiversity, and managing carbon stocks, all of which are critical for mitigating climate change impacts [4]. High-precision mapping supports the estimation of tree density, a vital metric given the species diversity and varied landscapes in tropical regions [5]. This capability directly influences ecological assessments, forest dynamics monitoring, and conservation strategy implementation [6].

From a management viewpoint, delineating tree crowns aids in detecting deforestation and degradation, enhancing the monitoring and preservation of tropical forests [7]. High-resolution remote

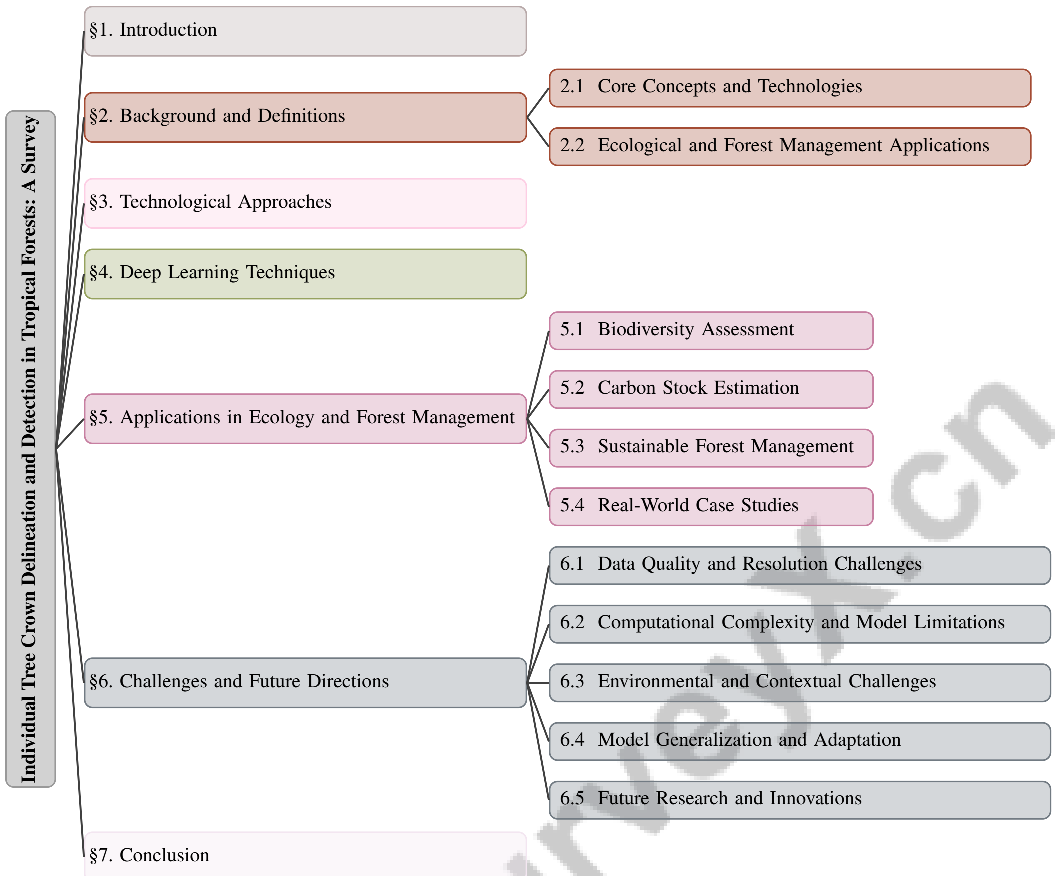


Figure 1: chapter structure

sensing technologies are essential for effective biodiversity monitoring and resource management, highlighting the importance of tree crown detection in ecological and forestry applications.

1.2 Role of Advanced Technologies

Advanced technologies, including LiDAR, UAV remote sensing, and hyperspectral imaging, have transformed forestry practices, particularly in delineating and detecting individual tree crowns in tropical forests. LiDAR is known for its ability to penetrate dense canopies, yielding high-resolution three-dimensional data critical for accurate forest mapping and management. When integrated with hyperspectral data, it significantly enhances tree crown delineation and species classification, improving our understanding of forest composition. This synergy enables effective identification of tree species and biomass estimation, essential for managing complex ecosystems like tropical rainforests. Machine learning classifiers and graph cut algorithms further leverage this data integration to analyze forest dynamics and biodiversity comprehensively [8, 9, 2].

UAV remote sensing has emerged as a vital tool, overcoming the limitations of traditional, labor-intensive forest assessment methods [10]. UAVs equipped with multispectral and hyperspectral sensors facilitate efficient collection of high-resolution imagery, crucial for detailed ecological monitoring and forest management [11]. The integration of deep learning techniques with UAV data has shown significant promise in enhancing tree species detection and health status classification, thereby supporting informed decision-making.

Hyperspectral imaging, capturing a broad spectrum of information beyond the visible range, is invaluable for species classification and monitoring in complex tropical environments [12]. When combined with LiDAR data, it enhances classification accuracy, making it a powerful tool for ecological studies and forest management [13]. Advanced machine learning techniques, such as deep convolutional neural networks, have facilitated effective classification of various objects within aerial imagery, showcasing their potential in forestry applications [14].

The development and application of these technologies have improved the precision and efficiency of forest management practices, democratizing access to sophisticated tools for comprehensive and cost-effective monitoring of forest ecosystems [15]. Bullock et al. emphasize the importance of incorporating contextual information into classification processes, highlighting these technologies' role in enhancing detection methods [7]. As the field evolves, integrating these technologies with innovations like Visual ChatGPT offers exciting prospects for advancements in remote sensing image processing and forest management [16].

1.3 Objectives and Structure of the Survey

This survey aims to systematically explore the methodologies and technologies employed in individual tree crown delineation and detection in tropical forests. By integrating insights from advanced remote sensing technologies and deep learning techniques, the survey elucidates their applications in enhancing ecological and forest management practices' precision and efficiency. It highlights the critical role of recent technological advancements, such as convolutional neural networks and multi-temporal remote sensing, in addressing the challenges posed by the complex canopy structures of tropical forests. These innovations are essential for monitoring individual tree species, assessing forest health, and supporting sustainable management practices amid climate change and biodiversity loss [17, 9, 18, 19].

The survey is organized into several key sections. The introduction outlines the significance of tree crown delineation and the transformative role of advanced technologies in forestry. The background section provides definitions and discusses core concepts and technologies relevant to tree crown delineation. The survey then examines technological approaches, focusing on the integration of LiDAR, UAV remote sensing, and hyperspectral imaging. Subsequently, it explores deep learning techniques, emphasizing models and algorithms that enhance detection and delineation processes.

Further sections discuss the practical applications of these technologies in ecology and forest management, supported by case studies and real-world examples. The survey also addresses challenges and future directions in the field, identifying areas for potential research and innovation. The conclusion synthesizes key findings, reiterating the importance of technological integration in advancing tree crown detection methodologies and suggesting avenues for future research and development.The following sections are organized as shown in Figure 1.

2 Background and Definitions

2.1 Core Concepts and Technologies

The delineation of individual tree crowns in tropical forests is enhanced by advanced technologies that improve mapping precision and efficiency. LiDAR is crucial for providing high-resolution structural data, essential for mapping complex canopies and estimating canopy height in dense environments. Techniques like the Online LiDAR System for Diameter at Breast Height (DBH) Estimation improve accuracy [20]. Integrating LiDAR with hyperspectral imaging refines tree crown delineation by offering detailed spectral information for species classification, though challenges persist with raster canopy height models potentially introducing inaccuracies [2].

Digital Aerial Photogrammetry (DAP) and RGB imagery offer high-resolution spatial data for detailed tree crown analyses [21]. UAVs, equipped with multispectral and hyperspectral sensors, revolutionize ecological monitoring by capturing high-resolution imagery vital for forest structural parameter estimation and health monitoring [10]. The combination of UAV imagery with deep learning techniques, such as probability heatmaps, enhances understanding of tree crown delineation [22].

Hyperspectral imaging's broad spectral range is invaluable for precise species classification, enhancing classification based on spectral and structural characteristics [12]. Deep learning techniques, including Convolutional Neural Networks (CNNs) and Vision Transformers (ViTs), are increasingly used for classification and segmentation in forestry. The Mask R-CNN, extending Faster R-CNN with a segmentation mask branch, is effective for instance segmentation [23]. Multiview Semantic Meshes

(MVSM) enhance classification accuracy by leveraging 3D mesh geometric information, enabling predictions from raw aerial images [24].

Fine-grained semantic segmentation in aerial imagery necessitates advanced techniques like deep learning to improve classification accuracy, exemplified by TreeSegNet's adaptive tree CNNs [25]. High-resolution multispectral imagery is emphasized for tree detection, offering advantages over LiDAR data [26]. Novel datasets like SYNTHTREE43K and CANATREE100 are crucial for training deep learning models, addressing challenges posed by limited labeled data [27].

The integration of these technologies enhances tree crown delineation and detection, supporting sustainable forest management and advancing ecological research. Classification of objects within high-resolution aerial imagery underscores the relevance of these technologies in diverse applications and highlights the need for advanced detection methods [28]. Automated linear disturbance mapping (ALDM), deep learning, and semantic segmentation are essential for understanding and managing forest disturbances [29]. Convolutional neural networks and context-aware techniques are critical for advancing tree crown delineation methodologies [7]. Utilizing high-quality hyperspectral reflectance spectra to derive relationships between vegetation indices and photosynthetic vegetation fraction (Fv) allows for more accurate performance assessments [30]. However, the scarcity of labeled data for training semantic segmentation models in multispectral remote sensing imagery remains a significant challenge, impacting the performance of algorithms reliant on deep convolutional neural networks [31].

2.2 Ecological and Forest Management Applications

Advanced remote sensing technologies, such as LiDAR, UAV imagery, and hyperspectral imaging, have significantly enhanced ecological and forest management practices by providing high-resolution data essential for precise tree species classification and forest health monitoring. These technologies facilitate the characterization of forest dynamics, crucial for sustainable management practices [32]. Diverse datasets, like FoMo-Bench, including multispectral, SAR, and LiDAR data, enable comprehensive forest monitoring across multiple tasks, supporting robust machine learning models for effective analysis of complex forest environments [33].

LiDAR and UAV imagery are instrumental in individual tree mapping, addressing challenges in detecting, localizing, and characterizing trees within dense canopies. This capability is vital for ecological applications such as carbon flux monitoring, where accurate canopy height assessments are essential for understanding carbon dynamics and ecological functions. In urban forestry, remote sensing technologies enhance automated tree species classification, contributing to urban ecosystem management and assessment of ecosystem services [34].

Hyperspectral imaging plays a pivotal role in ecological studies by enabling accurate classification of spectral information, essential for identifying plant species and assessing biodiversity. Extracting relevant spectral features and correlating them with ground-truth data supports predictions of plant species richness, aiding conservation strategies. However, the high dimensional nature of hyperspectral data poses analytical challenges, necessitating advanced deep learning techniques to utilize limited labeled training data effectively [35].

Accurate classification of high-resolution remote sensing images into semantically meaningful categories is crucial for various applications, including biodiversity assessments and conservation efforts [36]. Challenges in detecting objects in aerial images, such as significant scale variations and densely packed instances, are addressed through advanced object detection methodologies.

Advancements in these technologies not only improve the precision and efficiency of tree crown delineation but also support sustainable forest management practices, contributing to the conservation and resilience of forest ecosystems. By leveraging these tools, researchers and practitioners can make informed decisions that enhance the ecological integrity and sustainability of forest landscapes. The application of ALS in estimating carbon stocks is vital for conservation efforts and understanding the ecosystem services provided by tropical forests [37]. Moreover, UAV images and deep learning techniques facilitate the identification of tree species in complex ecosystems, such as Japanese mixed forests, addressing challenges posed by the diversity and complexity of these environments [3]. The potential of tools like Visual ChatGPT in analyzing and interpreting remote sensing images democratizes access to sophisticated tools, enabling broader participation in ecological research and forest management [16].

In recent years, the integration of advanced technological approaches in forestry has garnered significant attention due to its potential to enhance forest management practices. As illustrated in Figure 2, this figure delineates various technological strategies, prominently featuring the combination of LiDAR and photogrammetry, UAV remote sensing with multispectral imaging, and hyperspectral imaging through data fusion. Each segment of the figure underscores key applications and methodologies that contribute to improved tree crown detection, species classification, and overall forest management. By visualizing these complex interactions, the figure not only enhances our understanding of the technological landscape in forestry but also serves as a pivotal reference for future research in this domain.

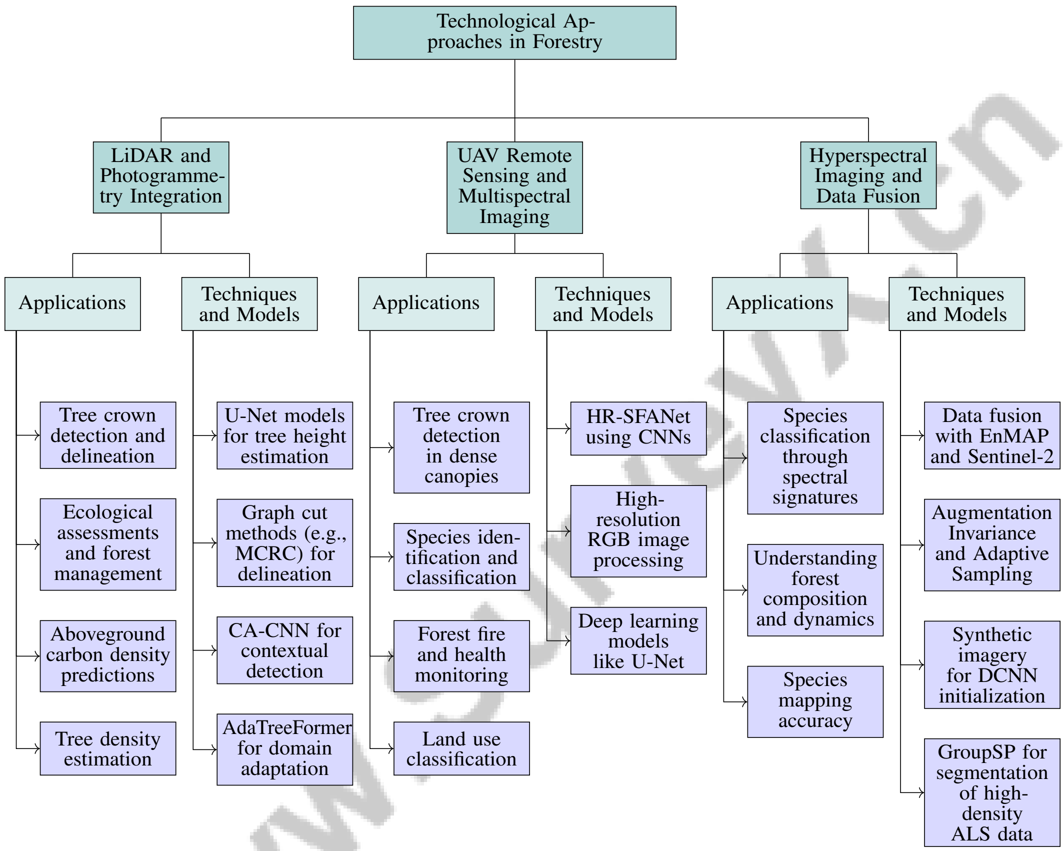


Figure 2: This figure illustrates the technological approaches in forestry, focusing on the integration of LiDAR and photogrammetry, UAV remote sensing with multispectral imaging, and hyperspectral imaging with data fusion. Each section highlights key applications and techniques/models that enhance tree crown detection, species classification, and forest management.

3 Technological Approaches

3.1 LiDAR and Photogrammetry Integration

The integration of LiDAR with photogrammetry is a critical advancement in forestry, enabling precise tree crown detection and delineation by combining detailed 3D structural data with high-resolution visual information [38]. This approach is particularly beneficial in tropical forests for ecological assessments and forest management. Techniques such as U-Net models effectively utilize this synergy to estimate tree heights and capture spatial features [1], while graph cut methods like MCRC enhance delineation by integrating LiDAR with hyperspectral data for a comprehensive forest view [2]. Machine learning models, including the CA-CNN, incorporate contextual information to improve detection, paralleling the benefits of LiDAR-photogrammetry integration [7]. Furthermore, combining LiDAR data with ground measurements improves aboveground carbon density predictions, highlighting its importance in biomass estimation [37]. Recent advancements like AdaTreeFormer address domain adaptation challenges, enhancing LiDAR and photogrammetry integration for tree density estimation [5]. This integration significantly refines tree crown delineation precision, supporting sustainable forest management by providing reliable data on forest composition and dynamics [39, 40, 41, 2, 9].

3.2 UAV Remote Sensing and Multispectral Imaging

UAVs combined with multispectral imaging present a transformative approach for tree crown detection in dense tropical canopies. These platforms capture high-resolution imagery crucial for ecological assessments and forest management [10]. Advanced machine learning methods, such as the HR-SFANet using CNNs, improve detection accuracy by processing multispectral imagery [26], while high-resolution RGB images exemplify UAV remote sensing's effectiveness in forestry [11]. UAVs are versatile, detecting and segmenting coconut trees in agricultural contexts [23] and monitoring forest fires and health [10]. Combining UAV remote sensing with deep learning models like U-Net enhances species identification and classification from aerial images [3]. This integration supports broader ecological applications, including land use classification, reflecting its potential for sustainable forest management and conservation [42].

3.3 Hyperspectral Imaging and Data Fusion

Hyperspectral imaging is essential for tree crown delineation in tropical forests, enabling precise species classification through unique spectral signatures [12]. Integrating hyperspectral data with LiDAR provides complementary structural insights, enhancing understanding of forest composition and dynamics [43]. Advanced methodologies dynamically extract fusion features, improving classification accuracy [43], while data fusion with EnMAP and Sentinel-2 enhances species mapping accuracy [6]. Techniques like Augmentation Invariance and Adaptive Sampling tackle hyperspectral imaging challenges, facilitating robust data processing [44]. Using synthetic imagery to initialize DCNNs enhances multispectral semantic segmentation, outperforming traditional methods [31]. Unsupervised methods like GroupSP combine deep clustering with ground-aware approaches for effective segmentation of high-density ALS data [45]. These technologies enhance tree crown delineation precision and contribute significantly to sustainable forest management and conservation, supporting informed decision-making and effective management strategies [30].

4 Deep Learning Techniques

4.1 Deep Learning Models and Instance Segmentation

Method Name	Model Architectures	Application Domains	Performance Metrics
U-Net[3]	U-Net	Tree Species Classification	True Positive Rates
MCRC[2]	Graph Cut Approach	Tree Crown Delineation	Boundary Recall
ATF[5]	Transformer-based Architecture	Tree Density Estimation	Precision, Recall
SMI-DCNN[31]	Deep Convolutional Networks	Semantic Segmentation Tasks	Mean-class Accuracy

Table 1: Summary of deep learning methods applied to tree-related tasks, detailing the model architectures, application domains, and performance metrics. The table highlights the versatility and effectiveness of various models, including U-Net and transformer-based architectures, in addressing ecological challenges through improved classification and segmentation accuracy.

Deep learning models, notably convolutional neural networks (CNNs), have revolutionized tree crown delineation and detection through robust instance segmentation capabilities, significantly enhancing accuracy in complex forest environments. Architectures such as U-Net have successfully classified tree species from UAV imagery, demonstrating their effectiveness in addressing classification challenges [3]. Table 1 provides a comprehensive overview of deep learning methods employed for tree species classification, crown delineation, and density estimation, illustrating the diverse applications and performance metrics associated with each model architecture. The integration of deep learning with remote sensing has improved forest decay detection and weed detection, underscoring their adaptability to various ecological challenges [11, 7].

Innovative methodologies like Multiclass Cut followed by Recursive Cut (MCRC) utilize deep learning and graph cuts to segment individual trees from 3D LiDAR point clouds, showcasing advancements in tree delineation [2]. The AdaTreeFormer model employs attention mechanisms and hierarchical cross-domain feature alignment, enhancing generalization across domains with fewer labeled examples, demonstrating the versatility of deep learning models [5].

Recent studies emphasize real-time semantic segmentation in remote sensing imagery, balancing high quality and efficiency, and highlight the need for advanced models that deliver both accuracy and speed [46]. Metrics such as Boundary Recall (BR) and Undersegmentation Error (UE) are crucial for evaluating segmentation quality, assessing deep learning models' performance in remote sensing applications [4].

The use of Digital Imaging and Remote Sensing Image Generation (DIRSIG) software to create synthetic multispectral images enhances the initialization of deep convolutional networks (DCNNs) for semantic segmentation tasks, improving training processes and outcomes [31]. By enhancing the accuracy and efficiency of ecological assessments, deep learning models play a pivotal role in conserving and bolstering forest ecosystems. Recent advancements significantly improve the identification of individual tree crowns, aiding in monitoring forest health and biodiversity, contributing to sustainable forest management practices and facilitating informed decision-making in ecological research [17, 47, 40, 41, 9].

4.2 Semantic Segmentation Techniques

Semantic segmentation techniques are crucial for enhancing tree crown delineation accuracy in remote sensing applications. Fully Convolutional Networks (FCNs), including the Nested Dense FCN (NDFCN) architecture, maintain high resolution throughout the labeling process, significantly improving fine detail distinction in aerial imagery [48]. Pixel-wise classification approaches utilizing context windows enhance segmentation performance by leveraging deep learning models to boost classification accuracy, highlighting the importance of contextual information in refining segmentation results [49].

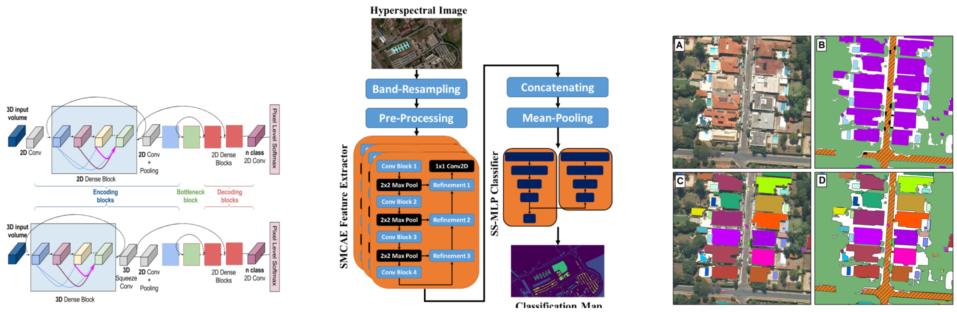
Interactive segmentation models like SimpleClick have emerged as efficient solutions for remote sensing applications. Tools based on these models, such as RSISeg, facilitate ecological monitoring and forest management, underscoring the potential of interactive segmentation techniques to streamline processes and enhance user experience [50].

Recent advancements in semantic segmentation techniques significantly improve tree crown detection in aerial imagery, advancing the broader field of remote sensing. Innovations such as the Crown-CAM method and deep learning algorithms like Mask R-CNN enhance accuracy and efficiency in analyzing complex forest environments. Crown-CAM provides interpretable visual explanations for tree crown detection, addressing previous localization and computational complexity limitations, while deep learning methods support high-resolution forest inventories at the individual tree level. These developments refine tree crown mapping and support applications including forest health monitoring and biodiversity assessments, contributing to effective environmental management and research [39, 46, 40, 41, 51]. Integrating these techniques into forest management practices supports informed decision-making and sustainable resource management.

As illustrated in Figure 3, semantic segmentation in deep learning encompasses diverse techniques tailored to specific applications. The first approach employs a 3D Dense Block within a 3D Convolutional Neural Network, demonstrating how multi-layer architectures process 3D volumes for enhanced feature extraction. The second example showcases a Sparse Multi-Channel Autoencoder (SMCAE) feature extractor paired with a Sparse Soft-Sampling Multi-Layer Perceptron (SS-MLP) classifier for hyperspectral image classification, highlighting a sophisticated flowchart beginning with band-resampling of input images. The third example focuses on urban planning and land use analysis, providing a comparative visual study of residential areas before and after land use standardization, underscoring the practical applications of semantic segmentation in urban design. Collectively, these examples emphasize the versatility and efficacy of deep learning techniques in addressing complex segmentation tasks across various domains [52, 53, 54].

4.3 Integration with Advanced Imaging Technologies

Integrating deep learning with advanced imaging technologies has transformed tree crown delineation, enabling more precise and efficient segmentation of complex forest environments. Hybrid fusion



(a) 3D Dense Block in 3D Convolutional Neural Networks[52]

(b) Hyperspectral Image Classification with SMCAE Feature Extractor and SS-MLP Classifier[53]

(c) Urban Planning and Land Use Analysis[54]

Figure 3: Examples of Semantic Segmentation Techniques

architectures exemplify this synergy by combining model-based and learning-based feature extraction techniques, enhancing the delineation process [55]. Such architectures leverage the rich data from advanced imaging technologies, including multispectral and hyperspectral sensors, to improve tree crown detection accuracy.

The Multi-resolution Multi-modal Sensor Fusion (MIMRF) approach processes raw LiDAR point clouds and fuses them with hyperspectral data, preserving data integrity by bypassing rasterization [56]. This method illustrates deep learning's capacity to handle and integrate diverse data types, enhancing the extraction of meaningful insights from complex remote sensing datasets.

Advancements include stacked multi-loss convolutional autoencoders for feature extraction, as employed by SuSA, enabling effective segmentation of remote sensing imagery even with limited labeled data [53]. This approach highlights the adaptability of deep learning models in data-scarce scenarios, leveraging semi-supervised learning techniques to improve classification outcomes.

The integration of deep learning with advanced modeling techniques, such as the Bayesian framework using Gibbs sampling, exemplifies innovative approaches in tree crown delineation [57]. Incorporating probabilistic models enhances segmentation task accuracy and robustness, supporting informed ecological assessments and forest management practices.

Incorporating fuzzy loss functions in semantic segmentation addresses class overlap challenges by utilizing Gaussian-convolved ground truth labels, refining segmentation accuracy [58]. This technique underscores the importance of advanced loss functions in improving deep learning model precision with complex remote sensing imagery.

Exploring superpixel segmentation methods combined with machine learning and citizen science aligns with advanced imaging technologies, enhancing deforestation detection and monitoring [59]. This integration not only improves tree crown detection and delineation but also supports broader environmental monitoring efforts.

The development of Stacked U-Nets, where each subsequent network refines the output of the previous one, exemplifies iterative segmentation accuracy improvement through deep learning architectures [60]. Such advancements highlight the continuous evolution of deep learning techniques alongside advanced imaging technologies, driving progress in remote sensing applications and supporting sustainable forest management initiatives.

5 Applications in Ecology and Forest Management

5.1 Biodiversity Assessment

Accurate tree crown delineation is crucial for biodiversity assessment, providing vital data on species distribution and forest structure. Advanced methodologies, such as higher-order active contour models, enhance tree crown delineation by effectively managing numerous circular objects, thus supporting ecological research and conservation strategies [61]. These techniques facilitate precise mapping of tree crown areas, improving our understanding of biodiversity patterns and dynamics.

Deep learning frameworks for automated tree health detection, including identifying dead trees, are essential for early forest health diagnostics, offering timely insights into forest conditions and contributing to biodiversity assessments. These advanced detection techniques, crucial for monitoring forest ecosystems and understanding the resilience of tropical rainforests to climate change, enable precise, taxonomically informed mapping of individual tree species and their health dynamics [17, 39, 41, 62].

Multiview methods enhance tree species classification accuracy, providing detailed insights into species distribution [24]. For instance, Mask R-CNN has successfully identified coconut trees in disaster-affected regions, showcasing the effectiveness of advanced detection techniques in biodiversity assessments [23]. Targeted change detection methods, identifying forest mortality from geometrid moth outbreaks, yield critical information on forest health and dynamics, further contributing to biodiversity assessments [63]. Additionally, models like TreeSegNet improve segmentation accuracy, essential for ecological monitoring [25].

The framework developed by Gominski et al. facilitates large-scale mapping of tree species with minimal human intervention, enhancing biodiversity assessment through reliable tree measurements and algorithm evaluation in forest monitoring. High-quality, customizable data further support algorithm development and evaluation, improving biodiversity assessments [64]. Recent advancements in tree crown detection technologies significantly enhance the precision and efficiency of biodiversity assessments, playing a crucial role in sustainable ecosystem management. Employing sophisticated methods like convolutional neural networks and multi-temporal remote sensing provides comprehensive insights into forest structure and species composition, facilitating informed decision-making regarding forest health, biomass, and carbon stock evaluations, thereby supporting ecosystem resilience against climate change and anthropogenic pressures [17, 40, 65].

5.2 Carbon Stock Estimation

Individual tree crown delineation is essential for accurate carbon stock estimation, a key component of sustainable forest management and climate change mitigation. Advanced remote sensing technologies, such as LiDAR and hyperspectral imaging, have significantly improved the precision of carbon stock assessments by enhancing the estimation of aboveground biomass and tree volume [8]. LiDAR systems capable of real-time diameter at breast height (DBH) measurements provide critical data for assessing tree biomass and carbon stocks [20].

Deep learning methods, including U-Net models, demonstrate high accuracy in estimating tree heights, crucial for biomass estimation. For example, tree heights in California were estimated with a mean error of 2.9 meters, highlighting the potential of these models to enhance carbon stock evaluations [1]. Moreover, integrating probability heatmaps in methods like PalmProbNet aids in visualizing palm distributions within dense forest canopies, supporting carbon stock estimation by elucidating biomass distribution [22].

The MCRC approach, which combines graph cuts with LiDAR and hyperspectral data, enhances tree delineation accuracy, vital for carbon stock estimation applications [2]. In urban settings, accurate classification of individual tree species significantly contributes to carbon stock estimation, as precise species data are crucial for understanding biomass distribution. A regional model for Borneo's forests exemplifies the importance of accurate carbon stock estimation in supporting carbon conservation and climate change mitigation efforts [37]. The method proposed by Amirkolaee et al. enhances tree counting accuracy, vital for carbon stock estimation in forest management [5].

The PRODES project dataset, comprising nine Landsat-8 satellite multispectral images labeled as 'forest' and 'non-forest', covering the Xingu River Basin in the Brazilian Legal Amazon, provides valuable data for evaluating and improving carbon stock estimation models [4]. By integrating these advanced methodologies and technologies, tree crown delineation not only enhances the accuracy and reliability of carbon stock estimation but also supports effective strategies for climate change mitigation and forest resource conservation.

5.3 Sustainable Forest Management

Individual tree crown delineation is pivotal for advancing sustainable forest management by providing accurate data on forest composition and health, essential for effective conservation and resource management strategies. The integration of hyperspectral and LiDAR data deepens our understanding of forest ecosystems, enabling detailed assessments that inform sustainable management practices [66]. This integration supports informed decision-making, ensuring the sustainable utilization of forest resources.

Advanced methodologies like HR-SFANet significantly contribute to urban forest management by providing high-resolution data that supports sustainable practices [26]. Accurate detection and classification of trees in urban environments facilitate better management and conservation strategies, bolstering urban forest sustainability. Moreover, the high accuracy and generalizability of land use classification methods highlight their potential to provide reliable data on land cover types, further supporting sustainable forest management [42].

The application of tree crown delineation in precision irrigation management underscores its role in enhancing sustainable agricultural practices, as evidenced by walnut water stress mapping [67]. This application illustrates the broader implications of tree crown technologies in promoting sustainability across sectors, including agriculture. Recent benchmarks emphasize the necessity of providing reliable tools for precision agriculture, leading to improved management strategies and crop yields [21]. These advancements not only bolster sustainable agricultural practices but also enhance the resilience and conservation of forest resources.

Integrating deep learning with remote sensing data offers substantial benefits for enhanced forest management practices, enabling precise and efficient monitoring and conservation of forest ecosystems. These technological advancements promote the resilience and sustainability of forest resources by facilitating the detection and characterization of tree decay levels and individual tree species through advanced remote sensing techniques, such as airborne LiDAR and deep learning. This ensures effective long-term conservation and management strategies, crucial for maintaining forest productivity, biodiversity, and ecosystem services amid natural and anthropogenic disturbances [17].

5.4 Real-World Case Studies

The application of advanced remote sensing technologies and deep learning methodologies has been illustrated through various real-world case studies, demonstrating their potential to revolutionize ecological monitoring and forest management. Youssef et al.'s method showcases adaptability for diverse applications, including wildlife monitoring and search and rescue, underscoring the versatility of advanced imaging techniques in addressing complex real-world challenges [55].

De Carvalho et al. present a novel dataset and effective methods for annotation and model training, highlighting the practical applicability of panoptic segmentation in remote sensing [54]. Such developments are crucial for advancing the precision of ecological assessments and supporting sustainable forest management practices.

PENet, as demonstrated by Tang et al., achieved significant improvements in object detection performance on aerial imagery datasets through its innovative architecture and methods [68]. This advancement illustrates the potential of cutting-edge models to enhance the accuracy and efficiency of remote sensing applications, providing valuable insights for ecological monitoring and forest resource management.

Moreover, the unsupervised multibranch capsule network model proposed by Xu et al. exhibits superior performance in extracting spectral-spatial-elevation features, indicating promise for practical applications in remote sensing data analysis [43]. This model's capability to process complex data highlights its potential for real-world applications in monitoring and managing forest ecosystems.

These case studies exemplify the transformative impact of integrating advanced technologies and methodologies in real-world applications, supporting informed decision-making and sustainable management of forest resources. The ongoing advancement and implementation of innovative technologies, such as deep learning and remote sensing, offer substantial potential for improving ecological resilience and fostering sustainable practices across various environmental settings. These innovations facilitate precise monitoring of forest health, enable the detection and classification of tree decay, and enhance biodiversity assessments, thereby supporting effective forest management and restoration efforts essential for combating climate change and preserving ecosystem services [17, 69, 70, 71].

6 Challenges and Future Directions

6.1 Data Quality and Resolution Challenges

Delineating individual tree crowns in tropical forests is hindered by challenges related to data quality and resolution, which are critical for accurate ecological assessments and effective forest management. High-resolution imagery is essential for capturing detailed tree crown structures, yet its availability is often limited due to geographic sparsity and dataset variability [10]. Complex datasets like DOTA further complicate detection algorithms, especially in densely packed or small instances [28].

A significant challenge is the imbalance and insufficiency of training data, particularly for invasive species such as black locust, complicating accurate classification [3]. The domain gap between source and target images also hampers model performance, as extensive labeled training data are required [5]. Reliance on synthetic data that may not represent real-world imagery exacerbates the synthetic gap, affecting performance [31].

High computational demands and slow inference speeds of current models limit real-time application deployment [46]. The use of decameter resolution multispectral imagery introduces nonlinear spectral mixing, inadequately capturing vegetation indices [30]. Atmospheric conditions, such as variable lighting and vegetation occlusion, further complicate tree crown detection and localization in high-resolution imagery [22].

Misclassification due to small-scale similarity problems can lead to detection inaccuracies [7]. The scarcity of annotated multispectral datasets and difficulties in sensor alignment and registration exacerbate these challenges, affecting tree crown detection reliability [26]. Lower-resolution imagery can obscure thinner linear disturbances, resulting in missed detections [29].

Addressing these challenges is essential for enhancing tree crown delineation precision, supporting informed ecological and forest management practices. Advancements in remote sensing techniques, particularly through UAVs and high-quality data acquisition, are critical for overcoming these obstacles, enhancing applications such as forest health monitoring, tree species classification, and biomass assessment, which are vital for sustainable forest management and effective carbon stock monitoring in the context of climate change [17, 10, 72].

6.2 Computational Complexity and Model Limitations

Advanced remote sensing technologies and deep learning models in tree crown delineation face challenges from computational complexity and inherent model limitations. Accurate tree species labeling and imbalanced datasets hinder detection performance in complex forest environments. The difficulty in obtaining expert-annotated labels can lead to reliance on noisy or unlabeled data, affecting detection accuracy. Annotation strategies and target-to-background ratios influence human annotator performance, leading to under-detection in sparse data scenarios, underscoring the need for robust methodologies and high-quality benchmark datasets to enhance deep learning approaches in forest mapping and species identification [62, 73, 74].

Extensive computational resources are necessary for thorough model evaluation, limiting accessibility for some researchers, particularly when processing high-resolution imagery. Computational intensity can lead to fragmented detections due to shadows and occlusions. The dependency on large labeled datasets for training deep learning models presents a significant challenge, as the scarcity of high-quality labeled data can affect model performance and generalizability. Training data characteristics in remote sensing can contribute to overfitting, restricting models' ability to generalize across varying environmental conditions. Recent studies emphasize the need for robust methodologies, such as knowledge distillation, to enhance model efficiency and performance [75, 76, 62, 72].

Increased parameters from multi-scale approaches heighten computational complexity, incurring higher costs. Hyperspectral data analysis challenges are particularly evident during dimensionality reduction, where efficient processing techniques, such as the novel unsupervised method for dimensionality reduction via regression (DRR), are essential. This method generalizes PCA by utilizing curvilinear features and effectively addresses issues related to collinearity and ill-determination, enhancing data representation interpretability. The integration of deep learning and knowledge distillation techniques highlights the necessity for advanced methodologies to optimize performance while managing the high dimensionality of hyperspectral imagery in practical scenarios [75, 77, 78, 35]. Data scarcity also affects model performance in specific tasks, such as detecting dead trees.

Performance variability based on environmental conditions and subjects' growth stages complicates achieving consistent and reliable model outputs. The dependency on cleanly labeled training data impacts performance, as evidenced by modest drops in certain categories due to class distribution challenges. High computational costs associated with methods like MCRC, which require solving eigenvalue problems for large datasets, represent a significant limitation [2]. Computational complexity is a notable limitation when dealing with extremely large datasets or unspecified spatial factors [79].

Addressing these computational and model limitations is crucial for advancing tree crown delineation and enhancing the precision and efficiency of remote sensing applications. Ongoing research aimed at improving computational processes and increasing machine learning model adaptability is essential for overcoming challenges in sustainable forest management. Leveraging advanced techniques, such as deep learning and remote sensing, can enhance forest monitoring capabilities, enabling accurate assessments of tree species, biomass, and forest health, which are vital for mitigating human impacts on forest ecosystems, understanding forest dynamics, and implementing sustainable practices that support biodiversity and carbon stock management. Integrating diverse open-access datasets, such as those cataloged in OpenForest, further facilitates data-driven approaches and encourages collaboration among scientists, fostering innovative solutions for large-scale forest monitoring and management [17, 47, 32, 72].

6.3 Environmental and Contextual Challenges

Detection and delineation of individual tree crowns in tropical forests are profoundly influenced by environmental and contextual challenges, complicating the accuracy and reliability of remote sensing methodologies. The inherent complexity of tropical forest canopies, characterized by dense vegetation and diverse species, complicates the extraction of precise tree crown information [2]. Variability in canopy structure and species distribution introduces significant noise in remote sensing data, necessitating advanced algorithms capable of distinguishing between overlapping crowns and varied spectral signatures [6].

Atmospheric conditions, including cloud cover and varying light conditions, further exacerbate these challenges by affecting aerial imagery quality and spectral data accuracy [22]. These factors can lead to inconsistencies in data acquisition, impacting tree crown detection model performance. Shadows and occlusions caused by taller trees or uneven terrain complicate the segmentation process, leading to potential misclassifications and inaccuracies [7].

Contextual variability in tropical forests, including differences in topography and microclimates, poses significant challenges for remote sensing technologies. These factors influence the spectral and spatial characteristics of imagery, requiring models to adapt to diverse environmental conditions to maintain accuracy [20]. The dynamic nature of tropical ecosystems, characterized by rapid changes in vegetation due to seasonal variations or anthropogenic activities, demands continuous monitoring and adaptation of detection methodologies [37].

Addressing these environmental and contextual challenges is crucial for improving the precision of tree crown delineation and detection in tropical forests. Advances in sensor technology, data fusion techniques, and adaptive algorithms are essential for overcoming these obstacles and enhancing the reliability of remote sensing applications in complex forest environments. Developing robust models that account for environmental variability and contextual nuances can improve ecological assessment accuracy and support sustainable forest management practices [10].

6.4 Model Generalization and Adaptation

The generalization and adaptation of models for tree crown delineation in tropical forests present significant challenges due to the diverse and complex nature of these ecosystems. Variability in forest structure, species diversity, and environmental conditions necessitates models that can accurately generalize across different datasets and adapt to novel scenarios. A primary challenge is the reliance

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on training data that may not fully capture the variability present in real-world environments, leading to models that perform well under specific conditions but struggle with new or unseen data [80].

The Point2Tree framework exemplifies this issue, as its performance can vary significantly when applied to datasets outside its initial training conditions. This highlights the need for diverse and comprehensive training datasets that encompass a wide range of environmental conditions and forest types to enhance model generalizability [80]. The challenge of domain adaptation is further compounded by differences in sensor modalities and resolutions, affecting the transferability of models trained on one type of data to another.

Rapid changes in forest environments due to natural and anthropogenic factors require models that can quickly adapt to new conditions. Creating adaptive algorithms that integrate real-time data and continuously refine their parameters is crucial for ensuring high accuracy in monitoring dynamic ecosystems like tropical forests, where advanced techniques such as neuroevolution-based classifiers and AI-driven plant segmentation are employed to detect deforestation and facilitate sustainable plant-clearing while coping with environmental variability and operational challenges [47, 71]. These algorithms must account for the inherent noise and variability in remote sensing data, impacting model performance and reliability.

To effectively tackle the challenges associated with tree crown delineation, it is essential to advance machine learning techniques such as domain adaptation and transfer learning. These methods enhance the robustness and flexibility of tree crown delineation models by enabling them to adapt to diverse environmental conditions and varying tree species distributions, as demonstrated by the AdaTreeFormer framework, which significantly improves tree counting accuracy across different domains. The application of convolutional neural networks, like the Mask R-CNN algorithm, has shown promising results in accurately detecting and delineating individual tree crowns from high-resolution satellite images, crucial for large-scale forest inventory and management [40, 5]. By enhancing the generalization capabilities of these models, researchers can ensure more accurate and reliable ecological assessments, supporting sustainable forest management and conservation efforts in diverse tropical environments.

6.5 Future Research and Innovations

Future research in tree crown delineation and detection should prioritize expanding dataset sizes and incorporating multi-temporal data to improve classification accuracy and model robustness across diverse ecological contexts [3]. Exploring satellite imagery alongside existing remote sensing technologies could significantly enhance the accuracy and scalability of tree crown detection methodologies. Advancements in specialized neural network architectures are crucial for achieving a balance between accuracy and speed, particularly in real-time applications [46]. Developing unsupervised domain adaptation techniques will further enhance model adaptability to varying environmental conditions.

Enhancing model robustness to seasonal changes is another critical area of focus, as it directly impacts tree counting accuracy in diverse ecological settings [5]. Future research should also explore strategies to develop more compact and regular superpixels from high delineation methods, thereby improving classification performance [4]. Optimizing network architectures and evaluating context techniques across different applications could lead to innovative advancements in tree crown detection methodologies [7].

Comparative analyses of vegetation indices using datasets from various sensors are essential for validating and extending current findings, enhancing the applicability of remote sensing technologies in ecological monitoring [30]. Future work should focus on enhancing synthetic data generation processes, exploring deeper network architectures, and integrating additional modalities to improve model performance [31].

By addressing these research directions, significant advancements in tree crown delineation can be achieved, supporting sustainable forest management and conservation efforts. These innovations will enhance the functionality and effectiveness of tree crown detection technologies across various environmental settings, enabling precise monitoring of tree health, decay levels, and species diversity, which are crucial for assessing biomass, biodiversity, and carbon stocks in the face of climate change and anthropogenic pressures [17, 41].

7 Conclusion

This survey delves into the evolving methodologies for individual tree crown delineation and detection in tropical forests, highlighting the transformative impact of advanced technologies and deep learning. The integration of LiDAR, UAV imagery, and hyperspectral imaging has revolutionized tree crown mapping, enhancing the precision of ecological assessments and forest management. Convolutional neural networks, with their robust segmentation capabilities, have further refined detection accuracy, proving instrumental in biodiversity assessments and carbon stock estimation.

Despite these advancements, challenges such as data quality and computational demands persist, necessitating continuous innovation in sensor technology and algorithm development. Future research should focus on expanding datasets, utilizing multi-temporal and satellite data, and developing adaptive neural network architectures to improve model resilience and applicability across diverse environments. By advancing these areas, significant strides in tree crown delineation can be achieved, supporting sustainable forest management and conservation efforts. The integration of these technologies promises to enhance forest ecosystem resilience and contribute to global biodiversity preservation and climate change mitigation.

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