Two Decades Progress on the Application of Remote Sensing for Monitoring Tropical and Sub-Tropical Natural Forests: A Review

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Abstract: Forest covers about a third of terrestrial land surface, with tropical and subtropical zones being a major part. Remote sensing applications constitute a significant approach to monitoring forests. Thus, this paper reviews the progress made by remote sensing data applications to tropical and sub-tropical natural forest monitoring over the last two decades (2000–2020). The review focuses on the thematic areas of aboveground biomass and carbon estimations, tree species identification, tree species diversity, and forest cover and change mapping. A systematic search of articles was performed on Web of Science, Science Direct, and Google Scholar by applying a Boolean operator and using keywords related to the thematic areas. We identified 50 peer-reviewed articles that studied tropical and subtropical natural forests using remote sensing data. Asian and South American natural forests are the most highly researched natural forests, while African natural forests are the least studied. Medium spatial resolution imagery was extensively utilized for forest cover and change mapping as well as aboveground biomass and carbon estimation. In the latest studies, high spatial resolution imagery and machine learning algorithms, such as Random Forest and Support Vector Machine, were jointly utilized for tree species identification. In this review, we noted the promising potential of the emerging high spatial resolution satellite imagery for the monitoring of natural forests. We recommend more research to identify approaches to overcome the challenges of remote sensing applications to these thematic areas so that further and sustainable progress can be made to effectively monitor and manage sustainable forest benefits.

Keywords: forests; remote sensing; satellite; monitoring; application

1. Introduction

Forests cover approximately one-third of the earth’s land surface area [1], and tropical and sub-tropical forests form a major component of the total area. Natural forests host diverse plant and animal species [2], cater to forages resources for insect pollinators [3], and help alleviate the effects of climate change by atmospheric carbon sequestration [4,5]. As many authors pointed out, forests provide various ecosystem services for people and the planet, including ecological, economic, social, and recreational functions at local, regional, and global scales [6]. Contextually, ecosystem services refer to the benefit that people derive from ecosystems and are co-produced through interactions between ecosystems and societies [7]. In developing countries, forests support millions of rural people’s direct livelihoods, providing food, medicine, fuel, fibre, non-timber forest products (NTFPs), and social and cultural functions [8,9]. The world’s largest tropical and subtropical forests are located in the Amazon region, followed by the tropical forests of Central and West African, termed as the Guinea-Congolian region, while the third-largest tropical forest region is located in Southeast Asia [10].

In recent decades, natural forests have been declining at alarming rates in most parts of the world [11]. As documented in many studies, humans are continuously changing land
use to access the planet’s resources through the clearance of forests for agricultural activities and urban expansion [12]. Furthermore, in developing countries, drivers of deforestation, including timber and fuel extraction, have been reported, along with evidence concerning underlying causes such as the economy, political instability, and governance [13]. These threats could modify forest ecosystems [14], and in so doing reduce their functions [15] and ultimately result in the extinction of tree species as well as species homogenization [16,17]. Thus, timely and consistent monitoring of natural forests is critical because their locations and conditions affect the local, regional, and global climate, and they have significant consequences for biodiversity and the well-being of millions of rural and urban people. Regular and accurate monitoring of natural forests’ spatial extents, species composition, physiological characteristics, forest cover change and drivers of change, and carbon content is essential to provide information for policy formulation, implementation of climate change-related agreements, monitoring sustainable schemes for timber extraction, and conservation management measures of natural forests [18,19].

Remote sensing has been utilized in a wide variety of applications confronting forest management and conservation sectors. The relevance and application of remote sensing for natural forest studies have been widely demonstrated by various authors. These applications include questions linked to forest biophysical parameter inventory, forest biochemical mapping [20], tree species discrimination and mapping [21,22], carbon stocks estimation [23–25], forest land cover change mapping [26–29], biodiversity assessment and monitoring [30–32], assessment of forest extent [33], and tree crown delineation [34–37].

An example of a review that has been important to remote sensing practitioners is Mutanga et al. [38], who showed the progress made in the application of remote sensing for the monitoring of vegetation in South Africa. It considered studies conducted from 1996 to 2015 on sensors and the type of vegetation with a focus on biomass, species discrimination, land cover, and vegetation quality. Though certain important aspects were covered in the review, it failed to assess studies conducted in other tropical and subtropical areas. Since many advancements have been seen in sensors, machine learning algorithms, and studies on the natural forests in tropical and subtropical regions, it is worth conducting a review that captures these advancements and areas of limitation. Therefore, our review paper covers a two-decade (2000–2020) period of progress made on the application of remote sensing in monitoring tropical and subtropical natural forests. The output of this review will provide information for forest managers, ecologists, and remote sensing experts on the advances made and shortfalls observed regarding the use of remote sensing imagery for monitoring natural forests in tropical and subtropical zones and how monitoring approaches can be improved.

2. Materials and Methods

A systematic search was conducted on the World Catalog, Scopus, ISI Web of Science, and Google Scholar databases to retrieve relevant articles. The search was conducted with a Boolean operator “AND” and a combination of keywords, which were “remote sensing” AND “forest cover” AND “classification” AND “mapping” AND “natural” AND “forest tree species identification” AND “biomass” AND “carbon” AND “diversity.” This search returned 6820 articles that were generally related to the keywords used for the search. The search was further conducted using similar keywords but restricted specifically to studies published between 2000 and 2020. This resulted in 1060 published articles. Thereafter, the titles and abstracts of the articles were assessed to determine their relevance to the study before downloading. Furthermore, articles about non-natural forests, such as plantations and duplicated studies, were removed, which led to a selection of 156 potential articles. The full text of these 156 articles was downloaded for further screening through reading the abstracts and full text and subjecting each article to the objectives of the review. Studies of global forests, urban forests, mangroves, savanna, and dry forests were excluded. The final screening resulted in 50 articles that fully met the criteria of article selection. The
search strategy, screening, and selection processes of the relevant articles are provided in a schematic diagram in Figure 1.

![Schematic Diagram of the Selection Process](image)

The 50 articles were further grouped into four thematic areas of remote sensing monitoring, which were (1) biomass and carbon stock estimation, (2) individual tree species identification, (3) tree species diversity prediction, and (4) forest cover mapping and change detection. In each of the articles, the focus was placed on the country of research, the type of remote sensing data employed, the algorithm used for mapping and modeling, and the accuracy produced.

3. Results

Figure 2 is a chart illustrating the number of studies carried out over the last 20 years under the four thematic areas considered under our review.

3.1. Aboveground Biomass and Carbon Estimation Using Remote Sensing

Several studies have utilized different sensors to predict aboveground biomass [39–41] and aboveground carbon [42–44] (Table 1). The majority of these studies were conducted in the tropical and subtropical forest regions of Asian countries such as China [42,45,46] and Nepal [43,44]. South America placed second in the number of studies conducted [40,47,48], with African tropical and subtropical forest regions lagging behind. We noted that the area and extent of the study sites ranged between 4 ha [39] and 6292.68 ha [49].
Table 1. Aboveground biomass and carbon estimation using remote sensing.

| Reference | Country       | Sensor Name       | Algorithm/Method | Area        | Accuracy         |
|-----------|---------------|-------------------|------------------|-------------|------------------|
| [39]      | Bolivia       | Quickbird         | LR               | 4 ha        | $R^2 = 0.70$     |
| [50]      | Hong Kong     | AVNIR-2           | SWR, LR          | 100 km²     | $R^2 = 0.88$     |
| [47]      | Costa Rica    | LiDAR, HYDICE     | OLS, GLS         | Not specified | RMSE = 32 t/ha  |
| [40]      | Yucatan Peninsula | LiDAR       | OLS               | 9 ha        | $R^2 = 0.89$     |
| [43]      | Nepal         | LiDAR, GeoEye-1   | LR                | 5821 ha     | $R^2 = 0.81$     |
| [42]      | Taiwan        | LiDAR             | MLR               | Not specified | RMSE = 0.91     |
| [51]      | Nepal         | Landsat 8         | RF, MLR          | Not specified | RMSE = 15–210 tons/ha |
| [48]      | Ecuador       | LiDAR             | LR                | ~85 km²     | $R^2 = 0.91$     |
| [52]      | India         | Sentinel 1 SAR,   | RF, SGB          | 400 km²     | $R^2 = 0.71$     |
| [45]      | China         | Sentinel 1 SAR,   | RF, ANN, GWR,    | Not specified | RMSE = 105.027 t/ha |
|           |               | Sentinel 2        | SVR               |             | $r = 1$         |
| [53]      | China         | Landsat 8, Landsat | RF                | 6.06 million ha | RMSE = 0.08 Mg/ha |
|           |               | TM                |                   |             | $R^2 = 0.73$     |
| [46]      | China         | Sentinel 1 SAR,   | SWR, GWR, ANN,   | 17,481 ha   | RMSE = 6.66 Mg/ha |
|           |               | Sentinel 2        | SVR, RF           |             | $R^2 = 0.97$     |
| [54]      | China         | Landsat 8         | LR, RF, XGBoost  | $13.00 \times 10^4$ km² | RMSE = 61.11 Mg/ha |
| [49]      | India         | MODIS             | LR                | 6292.68 km² | $R^2 = 0.94$     |
| [55]      | Ecuador       | Landsat 8         | PLSR              |             | $R^2 = 0.31$     |
| [44]      | Nepal         | GeoEye-1, RapidEye, LiDAR | MLR | 1888 ha | RMSE = 44 kg/tree |
| [20]      | India         | Sentinel 2        | RF, ANN, SVM     | 84.46 km²   | $R^2 = 0.86$     |

Note: HYDICE, Hyperspectral Digital Imagery Collection Experiment; SAR, Synthetic Aperture Radar; LiDAR, Light Detection and Ranging; AVNIR, Advanced Visible and Near Infrared Radiometer type 2; SWR, Stepwise Regression; GWR, Geographically Weighted Regression; LR, Linear Regression; MLR, Multiple Linear Regression; PLSR, Partial Least Squares Regressions; OLS, Ordinary Least Squares Ranning; AVNIR, Advanced Visible and Near Infrared Radiometer type 2; SWR, Stepwise Regression; GWR, Geographically Weighted Regression; LR, Linear Regression; MLR, Multiple Linear Regression; PLSR, Partial Least Squares Regressions; OLS, Ordinary Least Squares Ranging; GLS, Generalized Least Squares Regression; ANN, Artificial Neural Network; SVR, Support Vector Machine for Regression; RF, Random Forest; XGBoost, Extreme Gradient Boosting; SGB, Stochastic Gradient Boosting.
The majority of the studies identified by the selection criteria utilized optical sensor imagery to predict AGB and AGC. For example, Landsat 8 was utilized by many studies [41,53–55]. Other studies utilized high spatial resolution optical sensor imagery such as Quickbird [39] and Sentinel 2 [20]. Some other studies reviewed explored the capabilities of active sensor imagery, such as LiDAR [40,42,48]. We also identified studies that fused optical and active sensor imagery; for example, Wangda et al. [44] and Mbaabu et al. [43], fused Lidar data and GeoEye imagery to predict AGB. Sentinel-1 SAR and Sentinel 2 fusion were also utilized by a number of studies [45,46,52].

Non-parametric machine learning algorithms such as ANN [45], RF [53], SVR [45], and XGBoost [54] were utilized predominantly. By contrast, others used parametric algorithms such as LR [43], MLR [42], and OLS [40]. Overall, both types of algorithms produced satisfactory accuracy, but non-parametric approaches produced high accuracy for studies that adopted them.

Accuracies reported in the reviewed articles ranged from a coefficient of determination as weak as 0.31 [55] to a coefficient of determination as strong as 0.97 [46]. Studies that utilized a fusion of two sensors reported very good results [46,47].

### 3.2. Tree Species Identification Using Remote Sensing

The majority of the tree species detection studies were carried out in South American countries, including Brazil [30,56,57], Costa Rica [58–60], and Panama [61] (Table 2). Most of the studies in African tropical and subtropical regions were conducted in South Africa [62–64] and Ghana [19]. However, we identified fewer studies carried out in Asia [65,66]. In most cases, the studied forest cover area ranged from 70 ha [67,68] to 6000 ha [62].

**Table 2. Tree species identification using remote sensing.**

| Reference | Country   | Sensor/Data Set | Algorithm | Area       | Average Accuracy |
|-----------|-----------|-----------------|-----------|------------|------------------|
| [58]      | Costa Rica| HYDICE          | LDA, ML, SAM | Not specified | >92%             |
| [59]      | Costa Rica| HYDICE          | SMA       | Not specified | Not specified    |
| [60]      | Costa Rica| HYDICE          | RF        | Not specified | ≥85%             |
| [67]      | USA       | CAO-Alpha System, LIDAR | SVM | LDA, RDA, QDA, Linear-SVM, Radial-SVM, ANN, KN, | 70 ha | ≥90% |
| [68]      | USA       | CAO-Alpha System | LDA | Not specified | 73% |
| [56]      | Brazil    | ASD Spectroradiometer | LDA, Radial-SVM, RF | Not specified | 96% |
| [61]      | Panama    | DAP             | LR, Visual Analysis | 150 ha | 76% |
| [69]      | Hawaii, USA| EO-1 Hyperion  | MESMA, WESMA | 1500 ha | R² = 0.74, KC = 0.65 |
| [62]      | South Africa| WorldView-2 | SVM | 6000 ha | >89% |
| [63]      | South Africa| WorldView-2 | SVM, ANN | Not specified | >77% |
| [65]      | Taiwan    | QuickBird       | ML        | Not specified | SCKC = 0.99 |
| [30]      | Brazil    | AISA EAGLE, AISA HAWK, WorldView-3 | LDA, Radial-SVM, L-SVM, RF | Not specified | >84% |
| [66]      | China     | LiDAR          | RF        | Not specified | 86.2% |
| [19]      | Ghana     | AISA EAGLE, Sentinel 2 | SVM, ML | 815 km² | 92.34% |
| [64]      | South Africa| ASD Spectroradiometer, WorldView-2, RapidEye | PLS-RF | Not specified | >92% |
| [21]      | Brazil    | WorldView-2    | SVM        | 237.6 ha | 96% |
| [57]      | Brazil    | WorldView-3    | MESMA      | Not specified | ≥70% |

**Note:** CAO, Carnegie Airborne Observatory; SMA, Spectral Mixture Analysis; ML, Maximum Likelihood; SAM, Spectral Angle Mapper; LDA, Linear Discriminant Analysis; SVM, Support Vector Machine; RDA, Radial Discriminant Analysis; QDA, Quadratic Discriminant Analysis; AISA, Airborne Imaging Spectrometer for Application; DAP, Digital Aerial Photography; KC, Kappa Coefficient; SCKC, Species Conditional Kappa Coefficients; J–M, Jeffries–Matusita; ASD, Analytical Spectral Device; PLS, Partial Least Squares; MESMA, Multiple Endmember Spectral Mixture Analysis; WESMA, Wavelength Endmember Spectral Mixture Analysis.

Several studies used very high-resolution optical sensors, including WorldView-2 [21,62,63] and WorldView-3 [57]. Other studies used hyperspectral data such as HYDICE [58–60], Airborne Imaging Spectrometer for Application (AISA) EAGLE [19,30], AISA...
HAWK [30], and imaging spectrometer data [56,67–69]. Fewer studies used LiDAR [66] and digital aerial photography [61] for tree species identification.

Non-parametric and parametric statistical approaches were also utilized for tree species identification using remote sensing imagery. Machine learning algorithms such as RF [60,66] and SVM [19,21,67] were used, while others also used parametric types such as ML [58], LDA, QDA, and RDA [56,68].

The studies recorded high accuracies that ranged from 70% (Ferreira et al. 2019) to 96% (Ferreira et al. 2013, Wagner et al. 2018). Generally, the very high-resolution images had higher accuracies than most of the other image types.

3.3. Tree Species Diversity Mapping Using Remote Sensing

Africa had the highest number of tree species studies, with studies conducted in Sierra Leone [70] and Kenya [71,72] (Table 3). Studies in the Asian region had the second-highest number of studies, which were conducted in India [73], Kyrgyzstan [74], and China [75]. South America had the least number of studies, carried out in Panama [76]. The area of coverage was reported by three studies, ranging between 90 km$^2$ [74] and 850 km$^2$ [71].

| Reference | Country          | Sensor name                  | Algorithm       | Area        | Accuracy |
|-----------|------------------|------------------------------|-----------------|-------------|----------|
| [77]      | Malaysia         | Landsat TM                   | GRNN, MLPNN     | 300 km$^2$  | $r = 0.69$ |
| [78]      | Hawaii, USA      | AVIRIS                       | LR, MCS         | Not specified | $R^2 = 0.85$ |
| [74]      | Kyrgyzstan       | ASTER                        | DCA             | 90 km$^2$   | $R^2 = 0.61$ |
| [76]      | Panama           | Landsat ETM+                 | LR              | Not specified | $R^2 = 0.51$ |
| [73]      | India            | IKONOS, Landsat ETM+         | Not specified   | Not specified | $r = 0.33$   |
| [70]      | Sierra Leone     | AISA EAGLE                   | RF              | Not specified | $R^2 = 0.84\,9$ |
|           |                  |                              |     |             | RMSE = 0.30 |         |
| [71]      | Kenya            | Landsat-5 TM, Landsat-7 ETM+ | LR              | 850 km$^2$  | $R^2 = 0.36$ |
| [72]      | Kenya            | AISA EAGLE                   | $K$ Means       | Not specified | $R^2 = 0.50$ |
|           |                  |                              | clustering, LR  |             | RMSE = 3     |
| [75]      | China            | PHI-3, LiDAR                 | RF              | Not specified | $R^2 = 0.83,$ |
|           |                  |                              |     |             | RMSE = 0.25  |         |

Note: AVIRIS, Airborne Visible and Infrared Imaging Spectrometer; AIRSAR, Airborne Synthetic Aperture Radar; MCS, Monte-Carlo Simulation; DCA, Detrended Correspondence Analysis (DCA); PHI, Pushbroom Hyperspectral Imager; TM, Thematic Mapper; ETM, Enhanced Thematic Mapper Plus; GRNN, Generalised Regression Neural Networks; MLPNN, Multi-Layer Perceptron Neural Network; TM, Thematic Mapper.

Medium and high spatial resolution optical multispectral imagery was used for the tree species diversity mapping, for example, Landsat [71,73,76,77], ASTER [74], and IKONOS [73]. Some other studies are also explored hyperspectral data for tree species mapping, for example, AISA EAGLE [70,72] and AVIRIS [78]. Gillespie et al. (2009) fused Landsat ETM+ and AIRSAR to map tree species diversity.

Almost all the studies reviewed for this thematic area used LR, with the exceptions using GRNN, MLPNN [77], and RF [70,75]. The accuracies reported in the reviewed articles for the tree species diversity mapping ranged from a coefficient of correlation ($r$) of 0.36 [73] to an $R^2$ of 0.85 [78].

3.4. Forest Cover Mapping and Change Detection with Remote Sensing

As presented in Table 4, two studies were identified in Africa, which were carried out specifically in Nigeria [79] and South Africa [80]. The other studies carried out included one article in Southern America, in Belize [81], and three articles in Asia, in Bhutan [82], Bangladesh [83], and India [84].
Table 4. Forest cover mapping and change detection.

| Reference | Country     | Sensor Name | Algorithm       | Area   | Accuracy |
|-----------|-------------|-------------|-----------------|--------|----------|
| [84]      | India       | IRS-1 C WiFS | $k$-means      | Not Specified | 85%      |
| [83]      | Bangladesh  | SIR-C, ALOS PALSAR | ML             | Not specified | 83%      |
| [82]      | Bhutan      | Landsat ETM+ | ML              | Not specified | 87.5%    |
| [79]      | Nigeria     | Landsat 7 ETM+ | ML              | Not specified | 97%      |
| [81]      | Belize      | Landsat 8   | CART            | Not specified | 97%      |
| [80]      | South Africa | Landsat 8  | RF, SVM         | 2218   | 95%      |

Note: SIR-C, Shuttle Imaging Radar-C; ALOS, Advanced Land Observation Satellite PALSAR; WiFS, Wide Field Scanner; ML, Maximum Likelihood; HyMap, Hyperspectral Mapper; CART, Classification and Regression Trees.

We observed that the Landsat ETM+ and Landsat 8 were the most used sensors [79–82], whereas Rahman and Sumantyo [83] applied an active sensor. Most of the studies under this thematic area application employed ML [79,82,83]. A non-parametric statistical approach was adopted by Gyamfi-Ampadu et al. [80] for forest cover mapping and change detection. High accuracies were reported by these studies, the lowest of which was 83% [83] and the highest of which was 97% [79,81].

4. Discussion

Information-driven and evidence-based forest management and conservation are required to deal with the complex and dynamic nature of forests. Remote sensing approaches help bridge the gap between science and practice for monitoring and managing natural forests by providing resource information [85]. As a means of science approaches meeting practical needs, monitoring outcomes must be able to inform researchers, policymakers, and funding agencies to develop pragmatic and well-adapted conservation and governance initiatives and contribute to strengthening management actions and policy [85,86].

Our paper generally reviewed studies to ascertain progress made over the last two decades on remote sensing applications to monitoring of tropical and subtropical natural forests. Based on the applied search criteria, the majority of studies were conducted in South America, followed by Asia, while the lowest number of studies was found in Africa. Specifically, this paper reviews remote sensing studies for aboveground biomass and carbon estimation, tree species identification, tree species diversity, and forest cover mapping and change detection. We investigated questions such as the remote sensing sensor types used, methodology developed, and accuracy achieved.

The accurate and timely estimation of AGB and AGC are vital for carbon accounting and climate change policy direction, support of CO$_2$ emission monitoring, and forest management [24]. The outcomes of the AGB and AGC have a significant impact on local, regional, and global climate change policies [87]. Hence, natural forest AGB and AGC research have increased markedly over the last few years at various levels. Asia and Latin America produced more research while Africa lagged behind, which is detrimental to the execution of projects such as the Reduce Emissions from Deforestation and Forest Degradation (REDD+). Africa is one of the areas affected by climate change, thus making accurate information on the AGB and AGC vital in supporting decision-making.

Many studies accessed and used optical remote sensing data for AGB and AGC predictions. The data types included low, medium, and very high resolution, such as Landsat [54,55], Sentinel 2 [20], and GeoEye-1 [44], respectively. Recent advancements in some sensors such as the Landsat 8 have increased its sensitivity to vegetation [88,89], making it a suitable sensor for AGB and AGC estimation. The highly informative three red-edge bands included in the spectral bands of the Sentinel 2 increase its capabilities in carbon and biomass predictions. It is worth noting that the number of studies that used Landsat 8 and Sentinel 2 increased over time, and their wide-scale of coverage and free accessibility and affordability could be reasons for the increase [90]. Regarding hyperspectral data, numerous spectral bands provide it with many capabilities for predictions across different...
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Although hyperspectral data has many capabilities, it has limitations of saturation in dense natural forests and band redundancy, which can potentially negatively affect its predictive ability [92, 93].

Active sensors have been used quite extensively for AGB and AGC estimations, with the LiDAR being the most utilized [40, 42, 94]. This is because LiDAR data can provide tree height data for a reasonable estimation of tree volume and delineation of tree crowns. In addition, its combination with regression analysis and machine learning techniques produces better prediction outcomes [42]. The height and structural attributes data have the potential to support other data types for accurate estimates. In light of that, recent studies have employed the fusion of other earth observation data and LiDAR with the anticipation of improving results [47]. A limitation observed with AGC and AGB estimation is the covering of between 1 and 15 trees by emergent tree species in forest ecosystems [39]. Such trees are covered from the nadir of the sensors, and this could likely lead to incorrect and underestimation of AGC and AGB. Fusion methods involving LiDAR and other earth observation data could likely help deal with such problems. However, the commercial nature of LiDAR and hyperspectral data cause them to have limited accessibility and hinder their extensive use, especially in Africa [95].

The algorithms and statistical analyses employed are some of the factors that influence the accuracy of AGB and AGC predictions. The LR and RF algorithms remain the types used most often in AGC and AGB studies [43, 48, 50]. The parametric nature of LR makes it assume a normal distribution of data, whereas the non-parametric RF does not assume a normal distribution of data [96]. High accuracy was seen in all the studies, and as more advancements are realized in methodological approaches, accuracy will improve and continue to be high. More multi-temporal AGC and AGB studies are recommended since they help monitor changes in local carbon stock and biomass.

Tree species identification has become necessary due to factors such as species extinction and invasiveness. The accurate identification of tree species is vital for forest ecosystem management and conservation, especially for tropical and subtropical forests that are highly complex and diverse [66]. Moreover, it is of critical importance to the modeling of tree growth [97] and correct estimation of biomass and tree species diversity mapping [98]. Interestingly, Africa made much progress in identifying individual tree species research, which is vital for natural forest management and conservation.

Individual tree species identification is made possible with the advancement of very high spatial resolution imagery and the availability of LiDAR. The spatial resolution of remote sensing imagery is key in discriminating and identifying individual tree species. In selecting imagery for the identification process, the optimal resolution is likely to depend on the forest type and the methods applied [96]. Tree species discrimination is maximized when the pixel size of the utilized data gives room to depict the intrinsic spatial characteristics of the trees being examined [99]. Furthermore, the spectral properties on which tree species identification is carried out requires adequate spectral dissimilarity among species [72]. Unique spectral signatures are usually exhibited by tree species and are often linked to their biochemical and structural properties [100, 101]. Hence, there is an increase in species identification accuracy when spatial and spectral information is combined [68].

The recent advanced development in the spatial resolution of multispectral imagery has helped researchers move beyond the community-level mapping of tree species to individual-level species mapping [62]. Progress was made in the number of studies that employed VHR multispectral satellite imagery for individual tree species identification over the last decade. However, VHR satellite imagery, such as the WorldView-2 and Worldview-3, are highly used multispectral data for this kind of research; other types, such as the SkySat and Pleiades 1, are not making many breakthroughs in their application to tree species identification research, despite their high spatial resolution. It is likely that they are not known, or little information is available on them. We recommend that SkySat
and Plaeides 1 are also explored for individual tree species identification to ascertain their capability to discriminate between tree species and produce high accuracy.

It was observed that hyperspectral data were employed in the majority of the studies and produced high accuracy. This is likely a result of the ability of hyperspectral data to discriminate among various tree species because of the numerous narrow range bands that make them sensitive to trees and vegetation in general. Multispectral or hyperspectral data fusion with LiDAR was also an approach that produced higher accuracy in tree species identification. This method was used due to the combined ability of LiDAR and the hyperspectral data. The LiDAR can provide structural information, and hyperspectral data were identified to have high tree species separability abilities.

Different kinds of machine learning were applied, and they have become the main means of developing models for individual tree species identification. The SVM was the most used, which could be due to its robustness to noise, ability to deal with high dimensional data, lower training sample requirements, and fast prediction [96]. The non-parametric algorithms, such as the RF and the SVM, were found to perform better than parametric ones, such as the ML [102]. As such, some studies that used mixed input data variables, including spectral bands, vegetation indices, and texture variables, usually preferred to utilize non-parametric algorithms [37]. This has led to an increase in the use of non-parametric machine learning algorithms over time. Improved computational competencies enhance this trend through freely available new software, such as the R and Python statistical packages [96].

Tree species biodiversity mapping is also a high priority for natural forest management and conservation research as well as policy development [78]. Biodiversity is a broader concept than a count of the species present, as the species composition and their relative abundance are of equal importance [103]. These components of biodiversity are encompassed in the concept of tree species diversity. The monitoring and measuring of tree species diversity is a requirement for mitigating the loss of biodiversity and sustainable forest management [104]. Liang et al. [105] found a strong relationship between tree species diversity and basal area growth. It was observed to be related to the recruitment in stands of higher tree species diversity. Remote sensing has become a good source of information on tree species diversity at the landscape level over the years. The spatial distribution of the community of tree species is captured through modeling and prediction, with most of the reviewed studies over the last two decades conducted in Asian and African countries with a few in South America.

The medium spatial resolution of Landsat imagery can map the community of tree species; however, it cannot identify individual tree species. The Sentinel 2 was not used in any studies, but most recent studies, including Mallinis et al. [106], have shown its robustness for modeling tree species diversity. The authors found that Sentinel 2 performed better than RapidEye, which has a higher spatial resolution. Thus, it is recommended that the Sentinel 2 could be utilized for tree species diversity prediction due to its capabilities. The utilization of hyperspectral data and data fusion methods was an improvement in tree species diversity prediction, which could be due to their high sensitivity to tree species. New generation imageries such as the Planetscope, WorldView 2, WorldView 3, and TripleSat could also be adopted for tree species diversity for various natural forests as they may have the capability to produce improved prediction accuracy.

Concerning prediction algorithms, there was not much difference in those used in mapping in other thematic areas as LR was strongly preferred. The algorithms were able to produce satisfactory accuracy, and their preferential use could be related to their performance in many studies over the years. Despite the success achieved over the years in this thematic area, most studies have not considered phenological stages that manifest in different seasons and how they could enhance the prediction of tree species diversity. Accuracy is likely to improve through this method and it is hence worth considering such an approach. A limitation observed is the lack of information on the best season for tree species diversity predictions for tropical or subtropical natural forests. Emerging studies
may explore the identification of the best season when the condition of tree species captured in the imagery could improve the prediction accuracy.

Natural forest cover mapping and change detection monitoring are other thematic areas of research that are vital for forest management due to climate change, declining forest cover, and the increasing human population, which puts pressure on forests. Mapping the extent of forests provides information on their status that could support decision-making and initiatives meant to protect and conserve forests for the continual provision of ecosystem goods and services [80]. Remote sensing mapping of forest cover is restricted to spatially explicit broad classes of vegetation cover but not necessarily the individual tree species [107]. Forest cover mapping enhances the understanding of carbon sequestration and stocks, level of biodiversity, sustainability in natural resource utilization, and global change [108]. Information from forest cover mapping serves as the baseline for spatiotemporal change detection analysis of forest ecosystems. Similarly, increasing trends in deforestation, forest degradation, and fragmentation increase atmospheric carbon dioxide (CO₂) emissions, which contribute to climate change and global warming. Forest cover changes also have implications for the level of carbon stocks, biodiversity, and habitats [109]. Therefore, it is important for change detection analysis, which could help determine the extent of change over time and mitigation initiatives that could be adopted.

Researchers preferred the use of Landsat satellite imagery for both forest cover mapping and change detection analysis. The Landsat system has inherent uniqueness in the application for land cover mapping as it has longest uninterrupted Earth Observation program and was the first system to offer free global images [110,111]. The long history offers researchers the opportunity to gain vital insights on current and past trends in land cover change [111]. Its medium spatial and spectral resolution facilitates the detection of natural and anthropogenic changes on both local and regional scales [112]. Furthermore, it has a wide swath width of 185 km, which makes it a good image for landscape-level applications [38]. Researchers’ preference for it may be related to these reasons as well as its free availability, which enables financial resource-constrained researchers who cannot afford commercial imagery to access data that could enhance their research on forest cover mapping and change detection [113]. Forest cover mapping and change detection analysis planned within the next decade could explore imagery such as the Sentinel 2 and RapidEye, as they are also beginning to provide good, long-term archival imagery that can support such studies.

Concerning the classification algorithms, ML was applied in most of the studies, and high accuracy was produced [79,82,83]. RF and the SVM, which have proved to be robust for vegetation studies, also produced high accuracy in other studies [80].

5. Conclusions

Our review of the progress made in remote sensing application to forest monitoring over the past two decades presented interesting observations based on the thematic areas. Natural forest carbon and biomass, tree species identification, tree species diversity prediction, and forest cover mapping and change detection were observed to be key areas of remote sensing monitoring. The country of research, remote sensing data utilized, machine learning algorithm applied for modeling, prediction and classification, and the accuracy produced were assessed. More research is needed in Africa on carbon and biomass, as these are directly related to climate change. This is because Africa has been identified as one of the zones affected most by climate change.

Advancement was observed in the types of remote sensing data applied to the monitoring of the various thematic areas. More freely available data, such as Landsat and Sentinel 2 data, were used much in African countries, where there is less research funding, which hinders the utilization of commercial, very high resolution hyperspectral and active data for natural forest monitoring research. The machine learning algorithms that were used for the classification, modeling, and predictions contributed greatly to the high accuracy observed for most of the studies.
The outcome of this review is of importance to remote sensing researchers studying tropical and subtropical natural forests. The research outputs can guide the selection of remote sensing data and machine learning algorithms that can enhance research outputs. More research is recommended in these thematic areas and other relevant areas to provide adequate and credible information to forest managers and ecologists working toward efficient conservation and protection initiatives.

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