

Review

How Can Remote Sensing Help Monitor Tropical Moist Forest Degradation?—A Systematic Review

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Abstract: In the context of the climate and biodiversity crisis facing our planet, tropical forests playing a key role in global carbon flux and containing over half of Earth's species are important to preserve. They are today threatened by deforestation but also by forest degradation, which is more difficult to study. Here, we performed a systematic review of studies on moist tropical forest degradation using remote sensing and fitting indicators of forest resilience to perturbations. Geographical repartition, spatial extent and temporal evolution were analyzed. Indicators of compositional, structural and regeneration criteria were noted as well as remote sensing indices and metrics used. Tropical moist forest degradation is not extensively studied especially in the Congo basin and in southeast Asia. Forest structure (i.e., canopy gaps, fragmentation and biomass) is the most widely and easily measured criteria with remote sensing, while composition and regeneration are more difficult to characterize. Mixing LiDAR/Radar and optical data shows good potential as well as very high-resolution satellite data. The awaited GEDI and BIOMASS satellites data will fill the actual gap to a large extent and provide accurate structural information. LiDAR and unmanned aerial vehicles (UAVs) form a good bridge between field and satellite data. While the performance of the LiDAR is no longer to be demonstrated, particular attention should be brought to the UAV that shows great potential and could be more easily used by local communities and stakeholders.

Keywords: tropical moist forest; forest degradation; remote sensing; forest degradation metrics; forest resilience; forest structure; forest composition; forest regeneration

1. Introduction

1.1. Threats to Tropical Moist Forests

While unprecedented climate change is taking place on a global scale, mainly caused by human carbon emissions [1], and while the great majority of indicators of ecosystems and biodiversity are showing a rapid decline because of human drivers [2,3], forests are important to preserve. In particular, tropical forests that contain over half of Earth's species [4] and are among the terrestrial biomes with the largest flows of ecosystem services [5], on which billions of people depend [6]. Tropical forests also play a key role in global carbon flux by accounting for ~70% of the gross C sink in the world forests [7,8]. Yet, tropical forests are experiencing significant degradation [9], defaunation and deforestation [3,7,10], mainly caused by human activities [2]. Even if tropical forest loss is responsible for significant carbon emissions [11,12], these forests are today still considered as a carbon sink [7,13]. However, this trend could not continue over the next decades because carbon sink saturation will appear in tropical forests, firstly in the Amazon and secondly in Africa [13].

On a global scale, the decreasing of forests area only occurs in tropical regions [14], especially in tropical moist forests where 84 000 km² have been lost between 1982 and 2016 [15]. While more forests are under protection, Intact Forest Landscape (IFL), which is a “seamless mosaic of forest and naturally treeless ecosystems with no remotely detected signs of human activity and a minimum area of 500 km²”, and primary forests are still impacted by these changes [16,17]. The degradation of forests also covers significant areas with 20%, 63% and 65% that are considered as second growth forests after human activities, respectively in the Amazon Basin, Southeast Asia and Congo Basin [18]. Consequences are significant: biodiversity loss [19,20], soil degradation [21,22], negative impact on economic activities and households products [23,24], spread of diseases [25] and carbon emissions [7,26]. In tropical moist forests regions, drivers of forest degradation are timber logging, human-made fires, fuel-wood collection, small scale agriculture and mining activities [9,27,28]. In Central Africa, deforestation and degradation are linked to population density and agricultural activities, as well as access to resources, including mining, which promotes urbanization [10].

To mitigate climate change and biodiversity loss, and to stop degradation and deforestation processes, action must be taken at all levels—people, local, global—by all countries—poor, middle-income, rich—and in the same direction. Recently, the United Nations (UN) called to all sectors of society to mobilize for a decade of action with the aim to deliver 17 sustainable development goals by 2030. In particular, the 15th objective aims to ensure the conservation, restoration and sustainable use of forests [29]. Since 2008, the UN-REDD Programme (United Nations Reducing Emissions from Deforestation and Degradation Programme), set up under the United Nations Framework Convention on Climate Change (UNFCCC), promotes developing countries to protect their environment by adding value to the carbon stored in forests [30]. These objectives require the ability to localize, measure and monitor forest change and to define the two main causes of these changes: forest degradation and deforestation. Especially for the UN-REDD Programme, there is a need for a robust, transparent, consistent and accurate Measurement, Reporting and Verification (MRV) system to operate effectively [30,31].

1.2. Define and Measure Forest Degradation

While deforestation is the transformation from forest to non-forest area, over 50 definitions related to forest degradation were recently reported in peer-reviewed literature [32]. The IPCC (Intergovernmental Panel on Climate Change) defines forest degradation as “direct human-induced long-term loss (persisting for X years or more) of at least Y% of forest carbon stocks [and forest values] since time T and not qualifying as deforestation or an elected activity under Article 3.4 of the Kyoto Protocol” [33]. This definition only focuses on carbon stocks and depends on the individual country. This is also what the FAO (Food and Agriculture Organization of the United Nations) supports by letting countries define the term “degraded forest” [34]. The general definition of forest degradation refers to the reduction of the capacity of a forest to produce goods and services [35]. This definition leads to many interpretations and is linked to human benefits, meaning that if there is forest perturbation that does not impact humans, it will not be considered as forest degradation. This anthropocentric vision needs to be complemented by an approach that takes into account broader ecological processes regardless of their potential link with human societies such as forest dynamics and resilience [36,37]. Ecosystem resilience can be defined as the ability to recover the structure and function of its reference state after a disturbance and without external intervention [38]. While resilience and degradation are usually separately considered, they can be mixed by interpreting forest degradation through the frame of ecological resilience, and with reference to forest dynamics [36,37]. A degraded forest can be thus defined as “a state of anthropogenically induced arrested succession, where ecological processes that underlie forest dynamics are diminished or severely constrained” [36]. Whereas, degradation is a temporal process before the “degraded state” during which forests attributes decline (Figure 1). Indicators of forest degradation should reflect this ecological process. When a forest is resilient, these indicators can recover the reference state after disturbance, but the recovery takes more time if

disturbances are more intense and/or more frequent. The forest is losing resilience and so, is being degraded until a tipping point, at which the forest has reached the degraded state and cannot recover by itself.

Studying forest degradation through the frame of resilience involves defining reference states, indicators of resilience and benchmarks by which the forest is considered as degraded (Figure 1). The degradation process (upper part of Figure 1) can also be more accurately defined by measuring disturbances intensity and frequency. In the literature, reference state definitions and indicators of resilience vary following author and study objectives [36–38]. Degradation benchmarks are not well known as they involve having reached a point of no return for a specific ecosystem [37]. In light of these observations, compositional, structural and regeneration criteria can be analyzed to identify whether or not a forest is being degraded or is degraded [37]. Structure (e.g., canopy cover, diametric structure, biomass) and composition (e.g., specific richness, dominance of secondary species, presence of invasive species) give information about the forest state at a time. Studying forest degradation through the frame of resilience involves studying the phenomenon over time. Characterizing regeneration of a forest after disturbance (e.g., presence of shrubs, tree species or adult seed trees) can give information about forest future and its capacity to recover. For example, in the case of selective logging, forest composition can be altered: commercial species decrease while secondary species in logging gaps increase. Selective logging also induces changes in forest structure: loss in biomass, decrease of forest stands height and the emergence of canopy gaps. Regeneration after logging does not allow for restoring the initial forest composition: commercial species decline [39] and enrichment planting is needed to maintain them [40]. However, the biomass can recover quickly after disturbance [39,41]. It is so important to consider all three criteria (composition, structure, regeneration) to define whether a forest is degraded or not. Even though the regeneration of biomass suggests that the forest is resilient, it is not as if the initial composition cannot be restored without external interventions.

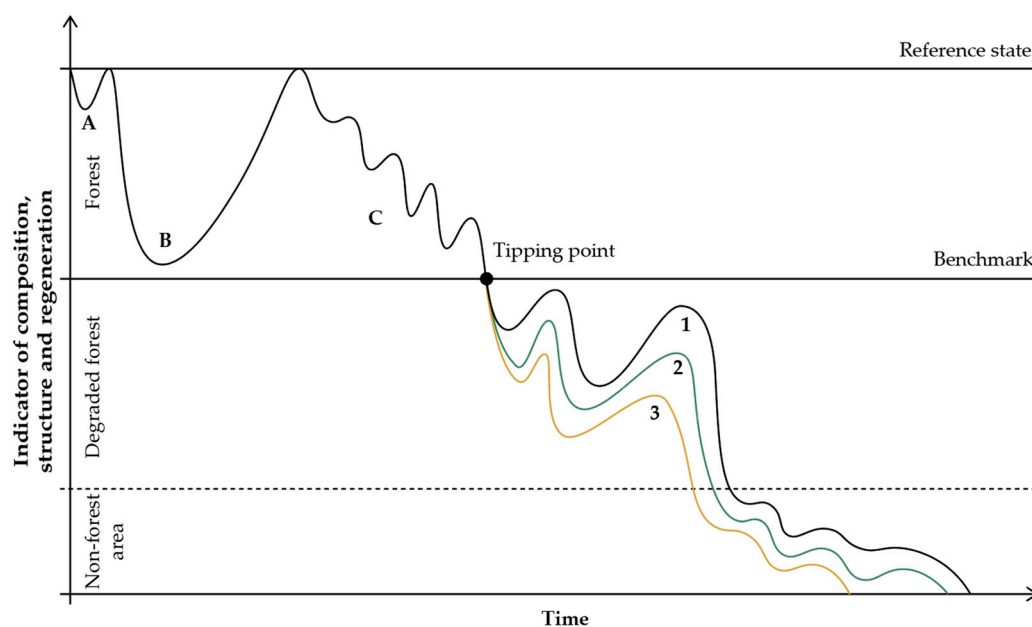


Figure 1. Forest transition curve illustrating the degradation process through the frame of resilience. The indicator of composition, structure and regeneration used to evaluate the degradation reflect the resilience of forests [37]. The curve illustrates variation of an indicator and its recovery to a reference state after a disturbance (A). If the disturbance is more intense, the indicator will take more time to recover (B), as well as if disturbances appear more frequently (C). Intense and/or frequent disturbances can lead the forest to a tipping point from which the forest will head towards a degraded state. The indicator value is below an expected level and the forest is considered as degraded. The curve 1, 2 and 3 represent different levels of forest degradation (adapted from [37,42,43]).

1.3. Remote Sensing to Measure Tropical Forest Degradation

Some documents are a good starting point to operationalize the definition of degraded forest in accordance with the IPCC guidelines [33,44]: the GOFC-GOLD (Global Observation of Forest and Land Cover Dynamics) sourcebook [45] and the methods and guidance from the GFOI (Global Forest Observations Initiative) [46] that focus on greenhouse gas emissions and carbon stocks variation in forests. Broader approaches consider several criteria together e.g., the production, the biodiversity, unusual disturbances, the protective function and the carbon storage of a forest [42]. Looking at degradation defined as a loss of resilience, adequate indicators of forest composition, structure and regeneration, as described in the previous section, need to be found [37]. Indicators requiring field data collection are time-consuming and logistically difficult to obtain. Especially in tropical moist forests that cover large areas, such indicators are difficult to access and are structurally complex. Remote sensing tools provide opportunities to more easily measure and spatialize indicators [47].

While deforestation is well detected on a global scale using different sensors and approaches, principally based on earth observation satellites [48], forest degradation, that appears at a smaller spatial and temporal extent, is more difficult to detect and to quantify. In recent reviews [49,50], different sensors (SAR, optical, LiDAR), image resolutions, spatial and temporal extents as well as indicators of degradation have been identified. Satellite data is the most used and improvement in mapping degradation should appear in the next few years by mixing SAR and optical data and by using very high-resolution data. SAR and LiDAR provide key information on forest structure and biomass in tropical forests. The different indicators measured with remote sensing are changes in canopy height and biomass, the presence of second-growth forests or canopy gaps as well as proxies like the presence of roads or villages often linked to forest degradation.

In the literature [49,50], indicators of degradation are not linked to the resilience concept and the use of unmanned aerial vehicles (UAVs) to monitor moist forest degradation is not mentioned. Yet the recent emergence of remote sensing techniques using an unmanned aerial vehicle (UAV) open a new field of research. Indeed, UAVs are able to produce 3D optical data from overlapping images at a very high resolution. This technology can also be taken in hand by local communities and actors (Community-Based Forest Monitoring [51]), allowing high temporal data acquisition and regular forest monitoring [52].

1.4. Objectives

Here, we propose to analyze remote sensing tools and approaches used to study tropical moist forest degradation throughout resilience criteria, on all spatial scales with all types of remote sensing tools (from local scale with UAV to pan-tropical scale with satellite data). The objectives are to (1) establish geographical repartition and spatial extent as well as temporal evolution of studies analyzing tropical moist forests degradation with remote sensing; (2) identify compositional, structural and regeneration criteria measured with remote sensing; (3) identify remote sensing indices and metrics used to detect tropical moist forest degradation.

2. Materials and Methods

2.1. Articles Selection

With the aim of finding all scientific articles studying tropical moist forest degradation with remote sensing tools, a systematic review was realized using the following inclusion criteria: (1) forest degradation is caused by human intervention; (2) remote sensing is used to detect forest degradation; (3) the study is localized in a tropical moist forest. In March 2019, the search expression in Table 1 was encoded in Scopus database and applied to titles, abstracts and keywords. The expression of research was adjusted until a good concordance between articles and inclusion criteria was found. The quality of this concordance has been verified with regards to the five most current keywords in the articles pool. In this case, “remote sensing”, “forest degradation”, “deforestation”, “tropical forest” and

“selective logging” were the most frequent. Relevant articles found after the research were added to the final pool. Then, articles published in French or in English, were sorted: first by deleting duplicates, second by screening titles and abstracts, third by reading the whole paper.

Table 1. Search expression encoded in Scopus database (March 2019) and applied to titles, abstracts and keywords.

Criteria		Search Expression
What?		degraded OR degradation OR disturbed OR disturbance OR altered OR alteration OR “secondary forest*” OR regeneration OR succession OR “second-growth forest*” OR “second growth forest*” OR “regrowth forest*” OR fragmented OR fragmentation OR “canopy gap*”
How?	AND	“remote sensing” OR lidar OR satellite OR sar OR radar OR image* OR uav OR “unmanned aerial vehicle”
Where?	AND	rainforest* OR jungle OR “tropical moist forest*” OR “equatorial forest*” OR “tropical humid forest*” OR “rain forest*” OR “central Africa” OR “congo basin” OR amazon* OR “southeast asia”
Limited to?		Articles
Date range		2000 to present

2.2. Article Analysis and Data Extraction

Selected articles were classified according to their geographical zone (Africa, America, Asia, Oceania and pan-tropical) and following their spatial extent: pantropical if the study zone covers more than one tropical basin, regional for various countries, national for a whole country, provincial for one or more province, landscape for an area over 10,000 hectares and local for an area below 10,000 hectares. Indicators of degradation measured by remote sensing were identified and classified following the compositional, structural and regeneration criteria. For example, structural criteria can refer to forest measurements such as canopy height, trunk diameter, canopy cover, crown width, trees density. Compositional criteria can refer to specific richness, biodiversity, abundance or to the absence of specific species. Regeneration criteria can refer to structural and compositional indicators that characterize regeneration as well as the age or stage of succession. Remote sensing indices and metrics were identified and grouped in different classes: spectral, textural, polarimetric or structural metrics calculated with 2D or 3D data, at sub-pixel, pixel or cell (i.e., aggregated pixels) scale.

3. Results

3.1. Geographical Repartition, Spatial Extent and Evolution over Time of Selected Articles

The research expressions (Table 1) encoded in Scopus in March 2019 matched with 919 articles (Figure 2). Sixteen relevant articles found by reading articles suggested by reviewers or published after the research, were added to the pool. In total, 10 duplicates were removed and abstract and title screening lead to the exclusion of 708 articles. Finally, 217 articles were fully read and 123 of them were selected to be part of the synthesis.

Two thirds of the studies selected in the final pool were localized in South or Central America. Degradation of other tropical forest basins is poorly studied (Figure 3). Most of the studies are carried out on a local or landscape scale on areas ranging from plots of a few hectares [53], to forest management unit (from 500 to 2000 hectares) [54,55], or areas delimited by remote sensing data acquisition footprint (e.g., Landsat tiles [56]). The few pantropical studies mainly focused on forest fragmentation [57–59], on degradation causes such as fires and logging [60] and on aboveground carbon density change [61]. There are still studies covering important surfaces. In the Congo basin, the area of forest loss due to disturbance drivers was estimated [27]. About 84% of forest degraded area is caused by small-scale and nonmechanized forest clearing for agriculture, followed by selective logging that accounts for 10%. In Amazonia, a regional biomass map was made by linking a canopy height model from remote sensing with an individual-based forest model [62]. Forest structure (basal area.ha⁻¹, stem diameter,

canopy height, number of trees.ha⁻¹) variation caused by tree-level to regional-scale disturbances can be therefore quantified. It thus provides a basis for large-scale analyses on the heterogeneous structure of tropical forests and their carbon cycle. In Southeast Asia, a fragmentation map was made of the whole region. Plantations of rubber and palm oil were taken into account, which is important in this region which contains most of such plantations in the world [63].

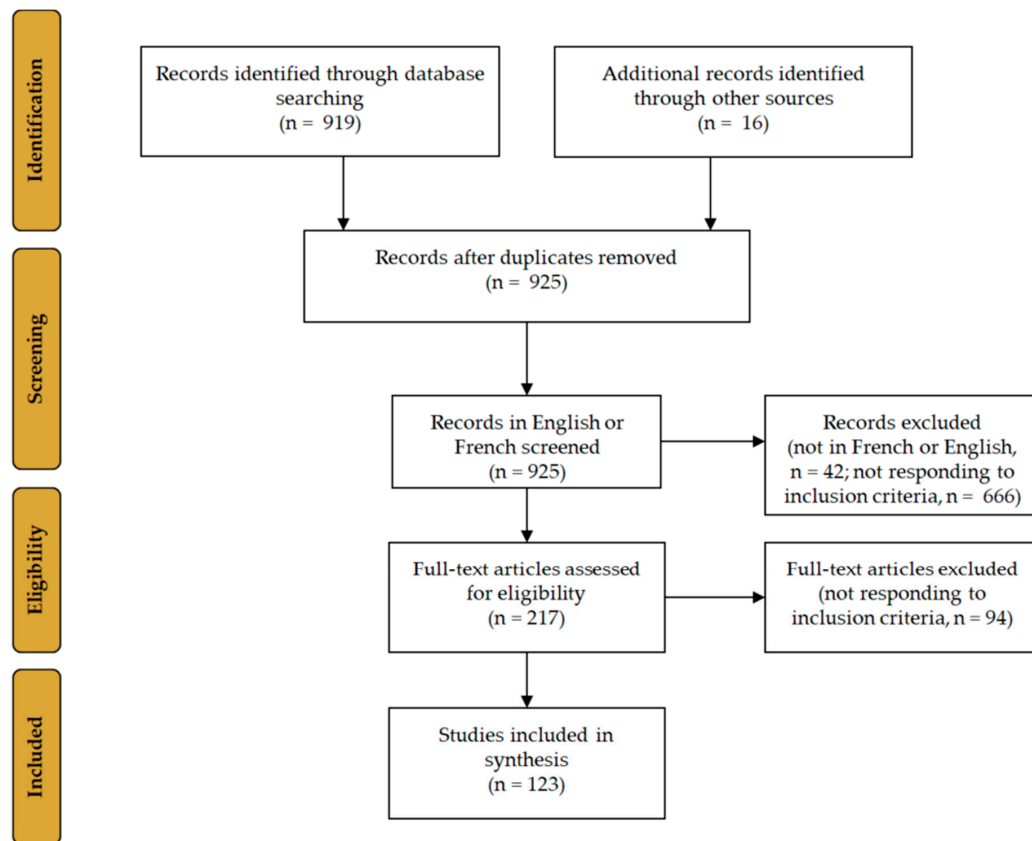


Figure 2. Study flow diagram (PRISMA) showing the flow of information through the different phases of the systematic review.

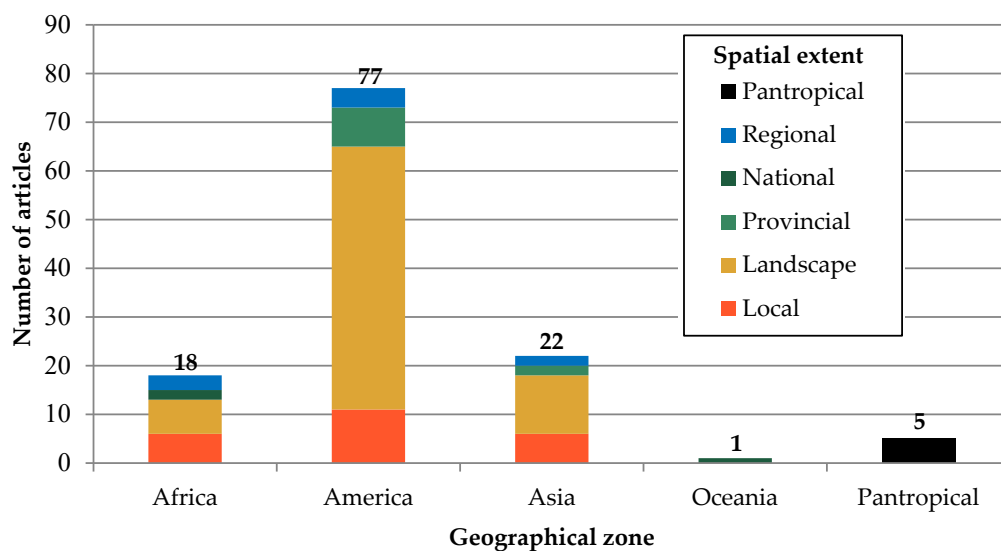


Figure 3. Frequency of articles according to their geographical area and their spatial extent.

The number of articles published about degradation remains stable until 2013, when a peak of 15 publications is noted (Figure 4). More than 50% of the studies were carried out after 2013 with an average increase of 10.4 studies compared to 3.8 studies in the year before 2013. The first studies, before 2004, took place in South America, more particularly in Brazil, and cover secondary forests [64], gold mining activities [65], fragmentation [66] and timber exploitation [67]. The number of articles on the Amazonian basin then increased steadily, with 3.9 studies per year, and remained the first studied zone compared to the other regions (Figure 4). The first study in the Congo basin was published in 2004 and concerned selective logging in the Central African Republic [68]. The average number of articles published per year remains very low for Central Africa, with a slight increase from 2013 onwards, from 0.4 (2004–2012) to 1.9 (2013–2019) studies per year. In Southeast Asia, the first study came later, in 2007, and concerns secondary forests [69]. The number of articles then increased continuously with an average of 1.7 (2007–2019) studies per year.

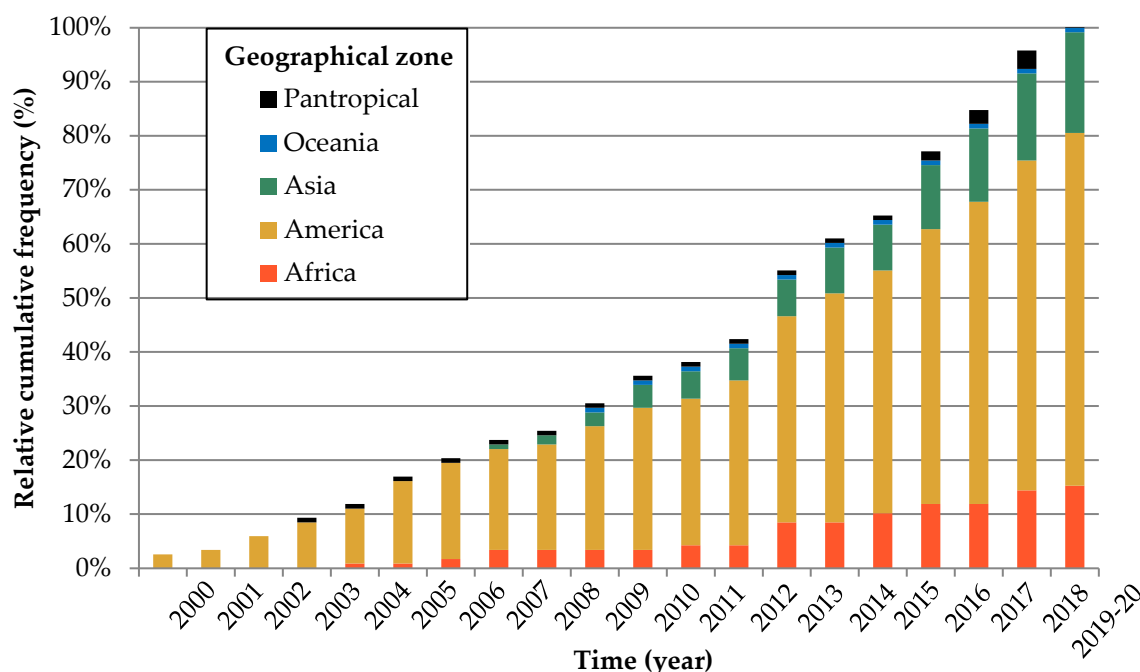


Figure 4. Relative cumulative frequency of articles according to time and to their geographical zone.

3.2. Indicators of Composition, Structure and Regeneration Measured with Remote Sensing

Among indicators of composition, structure and regeneration, structural indicators are the most used in studies monitoring tropical moist forest degradation (Table 2), particularly canopy gaps and landscape fragmentation. Fragmentation is the breaking of large, contiguous, forested areas into smaller pieces of forest and is influenced by large-scale phenomena e.g., roads extension, agriculture or mining developments [70]. Fragmentation appears to a large extent and so, is easily measurable with high-resolution (10–50 m) satellite data [63,71,72].

On the other hand, the detection and precise measurement of canopy gaps, which can appear at a smaller extent, requires LiDAR [73,74] data or very high-resolution optical images. In French Guiana, canopy gaps larger than 100 m² were detected using SPOT 5 images (10 m-resolution) [75]. In Ecuador, images coming from the same satellite were used to detect degraded forests with a canopy cover between 30% and 86% (general accuracy of 97.2%) [76]. In Costa Rica, canopy openings were detected ($R^2 = 0.82$ in relation to field data) on 26 plots of 0.25 hectares using a digital photogrammetric canopy height model (CHM), from UAV acquisition. In this study, portions of forests less than two meters in height were defined as a canopy opening [53].

High-resolution radar (SAR) data (10–50 m), although it offers good results [77], does not allow the detection of small disturbances [78]. High-resolution optical data underestimate canopy gaps [75]. More recently, Hethcoat et al. [79] developed a Random Forest machine-learning algorithm based on 30m Landsat images to detect pixels affected by timber harvesting in Brazil. This method allowed the detection of low-intensity selective logging ($<15 \text{ m}^3 \cdot \text{ha}^{-1}$; $1\text{--}2 \text{ trees ha}^{-1}$). Underestimation of canopy gaps can be limited by working at the sub-pixel level through spectral mixture analysis that provides different classes of fraction contained in a pixel [80].

A multitemporal approach also offers good results. In Brazil, Landsat 8 (30m-resolution) and Sentinel-2 (10m-resolution) imagery were used to detect canopy change caused by selective logging. They used a temporal approach by comparing images before and after disturbance. Both data show similar accuracy in selective logging detection with areas mapped as logged with Landsat imagery were considerably larger in comparison with Sentinel-2-based results [81]. In Cambodia and Laos, a comparison between two Landsat scenes was also performed to detect forest canopy disturbance and is able to highlight events as small as 0.005 ha [82]. In the Amazon Ecoregion, times series and sub-pixel analysis were performed on Landsat data to map deforestation, degradation and natural disturbance [83]. Finally, in Vietnam, the forest ecological vulnerability was assessed at the landscape scale [84]. Ecological vulnerability (V) depends on exposure to external stresses (E), sensitivity to perturbation (S) and capacity to recover or adapt (AC; $V = S + E - AC$) [85]. Imageries over 45 years (Landsat and Sentinel-2) were used to calculate indicators of S, E and AC based on evergreen forest, agricultural land proportion and fragmentation dynamics.

Above-ground biomass and carbon stock, integrating other structure parameters such as tree or stem diameter [86], are mainly used as indicators of forest degradation (Table 2). To model biomass, regressions between field measurements (e.g., above-ground biomass, volume, basal area, number of stems), at inventory plot or tree scale, and metrics from remote sensing data (aerial LiDAR [87], optical [88], radar [89]) are performed. In Borneo, above-ground biomass was calculated (Root mean square error (RMSE) = $20.3 \text{ tonnes} \cdot \text{ha}^{-1}$) by relating stem diameter to crown area. The crown was delineated by segmenting IKONOS images (1 to 4 m-resolution), with a segmentation accuracy of 39% for degraded forests [90]. Good results were also obtained by mixing different types of data, giving both spectral and structural information (optical and aerial LiDAR [91], optical and radar satellite with data saturation beyond $300 \text{ Mg} \cdot \text{ha}^{-1}$ [92]). In Myanmar, above-ground biomass variation, caused by selective logging, was measured using a photogrammetric digital surface model (DSM), from UAV acquisition, on two nine-hectare plots [93].

Measuring canopy height (CHM: Canopy Height Model, Table 2) with remote sensing requires normalizing the canopy top elevation (DSM) by subtracting the ground elevation (digital terrain model, DTM). This information (DTM and DSM) can be obtained using radar data according to the wavelength used: short wavelengths (e.g., X-band, $\lambda \sim 3 \text{ cm}$) do not penetrate the vegetation and reflect the top of canopy, long wavelengths (e.g., L-band, $\lambda \sim 23 \text{ cm}$ and P-band, $\lambda \sim 65 \text{ cm}$) pass through the vegetation and give information about the ground topography [77,94,95]. P-band could revolutionize forest structure knowledge around the world. This is the reason why the Biomass satellite (ESA mission, launch planned in 2022), that will be the first P-band SAR and the first radar tomographic space mission, will create a lot of opportunities. In some studies, SRTM (Shuttle Radar Topography Mission) of 30 to 90 m resolution, is used [77,94].

DSM and DTM can be calculated with very high accuracy by filtering upper and lower LiDAR returns [91,96]. When there are regular canopy gaps, the same discrimination can be achieved from photogrammetric point clouds, but with less accuracy. In Indonesia, a RMSE equal to 5 m to heights from LiDAR data was calculated on 48 and 82 hectares plots [97]. Another solution is to produce a DTM by interpolating GPS altimeter points taken in the field, which gives similar results to a DTM from LiDAR data [53]. The latter solution depends on the structure and nature of the forest cover, which will strongly influence the quality of reception of the GPS signal on the ground.

Table 2. Indicators of composition, structure and regeneration with the number of articles using them and examples in the references column.

Indicators	Number of Articles	References
Structure		
Canopy cover	2	[99]
Canopy gaps and cutting area	12	[79]
Landscape fragmentation (patches number, area and perimeter, fractal dimension)	17	[57,58,72,100]
Forest density	1	[63]
Connectivity	1	[63]
Above-ground biomass and carbon stock	22	[101]
Canopy height	4	[102]
Composition		
Pioneer and climax species groups	1	[98]
Regeneration		
Secondary forest age	8	[94]
Area of secondary forests	3	[103]
Succession stage	10	[89]

The compositional criterion is not commonly measured in articles studying the degradation of tropical moist forests that are structurally complex and rich in species, and so difficult to identify (Table 2). In Borneo, Landsat imagery cannot effectively detect subtle intra-guild trait variation (e.g., trait variation within climax guild) because of the low spatial/spectral resolution. However, Landsat imagery has been proven to be able to detect inter-guild trait differences (i.e., trait differences between pioneer and climax guilds). A composition gradient is then linked to a degradation gradient [98].

3.3. Remote Sensing Metrics and Indices Used to Detect Tropical Moist Forest Degradation

Metrics and indices can be calculated in order to highlight some aspects (e.g., soil, vegetation, height, granularity, etc.) of remote sensing data. In this study, textural metrics were first noted. In remote sensing, texture refers to the spatial variation of image greyscale levels. Visual and qualitative characteristics of an image, e.g., roughness, granularity or contrast, can be expressed with quantitative statistics measurement called textural metrics. Mobile windows, which are squares moving on the imagery, allow comparisons between pixels and its surroundings [104,105]. Two kinds of metrics are usually used: (1) the first-order ones that are statistical properties calculated within a certain window (e.g., the mean, the standard deviation, etc.) and therefore do not consider pixel neighbor relationships; (2) the second-order metrics that consider the spatial relations between groups of two neighboring pixels within the window. These last metrics are the most frequent in papers noted in this study. It requires calculating Gray-Level Co-occurrence Matrices (GLCM) which are “matrices containing the probabilities of co-occurrence of pixel values for pairs of pixels in a given direction and distance” [106]. The following second-order textural metrics were noted in this study [105–108]:

- The variance which measures global variation in the image. Large values denote high levels of spectral heterogeneity (salt and pepper effect);
- The contrast which is a quadratic measure of the local variation in the image. High values indicate large differences between neighboring pixels;
- The dissimilarity which is a linear measure of the local variation in the image. Low values indicate homogenous texture;
- The homogeneity which measures the uniformity of tones in the image. High values indicate homogenous texture;
- The entropy which measures the disorder in the image. High values indicate disorder;
- The angular second moment which measures the order in the image. High values indicate order;
- The correlation which measures the linear dependency between neighboring pixels.

Spectral indices combine spectral reflectance from two or more wavelengths which indicates the relative abundance of features of interest. Vegetation index are the most common in studies measuring moist tropical forest degradation:

- The “Aerosol Free Vegetation Index” (AFRI) allows the assessment of vegetation and biomass burned in the presence of smoke and other anthropogenic pollution [109,110];
- The “Enhanced Vegetation Index” (EVI) from MODIS satellite data is sensitive to canopy variations in high biomass regions where the “Normalized Difference Vegetation Index” (NDVI) saturates. When degradation is strong and closer to deforestation (e.g., fragmentation), the NDVI better highlights disturbances [111,112];
- The “Global Environment Monitoring Index” (GEMI) was developed to assess vegetation by minimizing atmospheric effects and is sensitive to soil background [109,113]. Matricardi et al. [109] showed that a modified GEMI could be a reliable estimator of fractional canopy coverage, as well as the “Modified Soil Adjusted Vegetation Index aerosol resistant” (MSAVI_{af}) that minimizes soil background influences [114];
- The “Green-Red Vegetation Index” (GRVI) that increases the contrast between photosynthetic active surface and bare soil surface and shows a distinct response to subtle disturbance [115,116];
- The “Normalized Difference Water Index” (NDWI) was developed to monitor water in vegetation and therefore can detect hydric stress in forests [117,118].

Some spectral indices directly focus on the disturbance (Table 3) such as the “Normalized Burn Ratio” (NBR) which highlights burned areas [119]. A difference between two NBR (Δ NBR) can also be used to assess forest disturbance that appears between two dates [81,82]. The “Forest Disturbance Index” (FDI) assumes that the soil of a disturbed forest will be more exposed than a conventional forest, resulting in more brightness and less wetness and greenness [120].

Table 3. Spectral indices used in the detection of tropical moist forest degradation.

Indices	Description	Reference
<i>- at pixel scale</i>		
Normalized Burn Ratio (NBR)	$\frac{p_{NIR} - p_{SWIR}}{p_{NIR} + p_{SWIR}}$ where SWIR wavelength is between 2.05 and 2.45 μ m [124]	[119,124]
Forest Disturbance Index (DI)	$B_r - (G_r + W_r)$	[120]
<i>- at sub-pixel scale</i>		
Canopy gap fraction	Depends on gap fraction and needing calibration with field data	[121]
Normalized Difference Fraction Index (NDFI)	Adapted to selective logging and forest fires: $\frac{GV_{shade} - (NPV + SOIL)}{GV_{shade} + NPV + SOIL}$ where: $GV_{shade} = \frac{GV}{100 - SHADE}$	[122]
Forest Degradation Index (DEGRADI)	Highlights disturbed forests area: $G \frac{Soil}{GV} + Off$	[123]

where: p : reflectance, NIR: near infrared band, SWIR: short-wave infrared band, G: gain factor, Off: offset, SHADE: shadow and burned area fraction, B_r : re-scaled brightness [120], W_r : re-scaled wetness [120], G_r : re-scaled greenness [120], GV: pixel green fraction.

Sub-pixel spectral indices are also widely used to highlight disturbances in forest area. Through spectral mixture analysis, class fraction in a pixel can be extracted. Pure pixels, called endmembers, are used as spectral reference for each class. Their selection must be done carefully with the help of the “Pixel Purity Index” (PPI) for example [109]. For forest area, common classes are soil (SOIL), non-photosynthetic vegetation (NPV), green (GV), shadow and burned area (SHADE). Pixel fractions are then used to calculate sub-pixel indices (Table 3). The canopy gap fraction, measured on field, depends on the pixel green fraction calculated with the CLAS (Carnegie Landsat Analysis System) algorithm [121]. The “Normalized Difference Fraction Index” (NDFI) summarizes non-photosynthetic vegetation, green and soil fraction and is well adapted to selective logging and forest fires [122].

The forest degradation index (DEGRADI) underlines the spectral contrast between soil and green fraction in a pixel [123].

Polarimetric indices calculated from radar data [89,94,125] are also used. Indices commonly used are summarized and described in [89]: the parallel polarization ratio (Rpp) and the cross-polarization ratio (Rcp) [126], the radar vegetation index (RVI) [127], the polarization fraction (PF) [128] and the pedestal height (PH) [129]. Some polarimetric indices are directly related to forest degradation and their compositional, structural and regeneration criteria (Table 4) such as the radar forest degradation index (RFDI) [89,130], the vegetation scattering index (VSI), the biomass index (BMI) and the canopy structure index (CSI) [131].

LiDAR and photogrammetric point clouds can be used to calculate metrics reflecting the 3D structure of the forest. Beyond statistical coefficients [87], other metrics can be calculated such as the “Relative Density Model” (RDM) [54] which detects whether the undergrowth, belonging to a user-defined range of heights, has been impacted (Figure 5). It is calculated by dividing the number of points between the upper and lower limit by the sum of these points with the number of points below the lower limit [54,87]. The “Topographic Position Index” (TPI) is an indicator of the topography, reflecting the position within the landscape (e.g., valley bottom or crest) [97]. The TPI is calculated with a moving window (150 × 150 m [97]) in which elevation of the central pixel (x) is compared to itself and the surrounding pixel elevation (X , $n = 9$).

$$\text{TPI} = x - \frac{1}{n} \sum_{i=1}^n X_i, \quad (1)$$

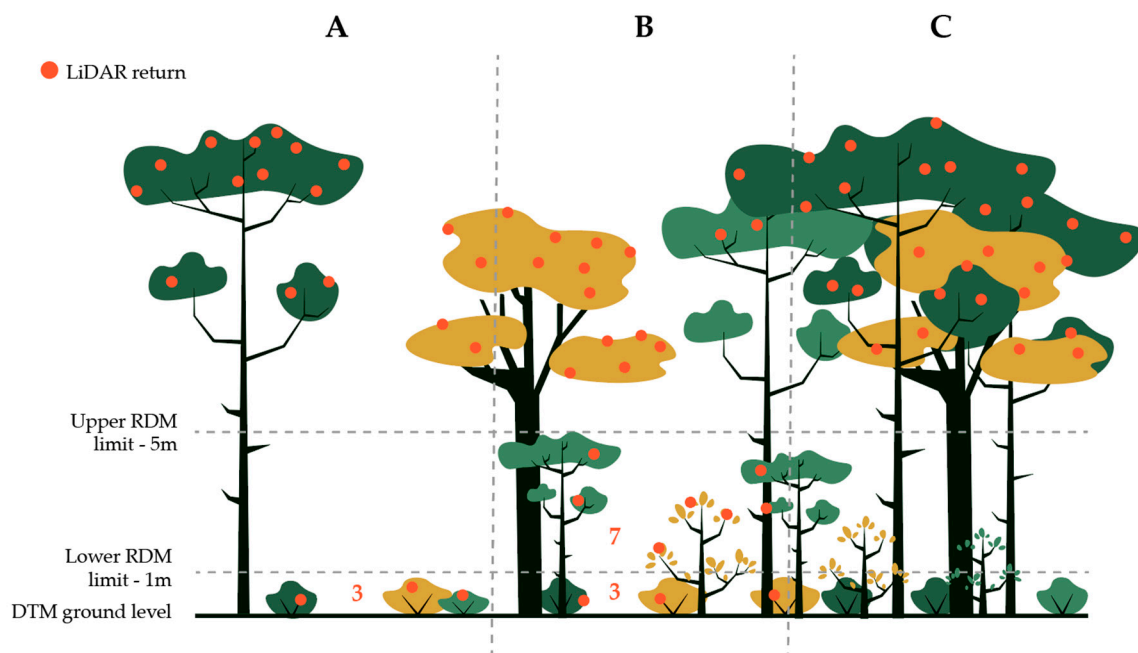


Figure 5. Illustration of relative density model (RDM) calculation method (Number of returns between the upper and lower RDM limits/Number of returns between the ground level and the upper RDM limits). (A) The RDM is equal to $0/(0 + 3) = 0$, indicating that the undergrowth has been crushed or removed. (B) The RDM is equal to $7/(7 + 3) = 0.7$, indicating intact undergrowth with little or no disturbance of vegetation in the 1–5 m range of heights. (C) The RDM is equal to $0/(0 + 0) = \text{undefined}$, indicating the forest is very dense, with an intact canopy not disturbed.

Table 4. Polarimetric indices used in the detection of tropical moist forest degradation.

Indices	Description	References
Radar Forest Degradation Index (RFDI)	Highlights canopy cover variation: $\frac{\sigma_{HH}^0 - \sigma_{HV}^0}{\sigma_{HH}^0 + \sigma_{HV}^0}$	[89,130]
Biomass Index (BMI)	Links leaf (crown) biomass to woody biomass: $\frac{\sigma_{HH}^0 - \sigma_{VV}^0}{2}$	[89,131]
Canopy Structure Index (CSI)	Relative importance of vertical versus horizontal structure of vegetation: $\frac{\sigma_{VV}^0}{\sigma_{HH}^0 + \sigma_{VV}^0}$	[89,131]
Vegetation Scattering Index (VSI)	Canopy thickness and density indicator: $\frac{\sigma_{HV}^0}{\sigma_{HV}^0 + BMI}$	[89,131]

où: σ^0 : backscatter coefficient in decibel dB, polarization HH: horizontal electric wave for both emission and reception, polarization HV: horizontal electric wave for emission and electric wave for reception, polarization VV: vertical electric wave for both emission and reception.

4. Discussion

4.1. Temporal Evolution, Geographical Distribution and Spatial Extent of Forest Degradation Studies Using Remote Sensing Tools

The number of papers measuring tropical rainforest degradation by remote sensing is low, with only 123 papers meeting the inclusion criteria. In contrast to its counterpart, deforestation, which is now well documented and spatialized [15,132], degradation is less known because it is difficult to detect and poorly defined [9,133,134]. There is in fact no scientific consensus on the concept of forest degradation, leading to a large number of definitions and multiple ways of measuring it, particularly by remote sensing, as demonstrated in this literature review. Studying degradation from the point of view of forest dynamics and resilience opens up many opportunities and more challenges. This would make it possible, in particular, to generalize and isolate this definition from any preconceived ideas put forward by humans [36,37].

Tropical moist forest degradation is mainly studied and monitored in South America. The degradation of forests in Central Africa and Southeast Asia is hardly studied, which does not mean that the phenomenon is not present. This trend is not specific to degradation, but is also found in other fields of study, for example in hydrology [135] or in agroforestry [136]. However, degradation is more significant in the forests of Central Africa and Southeast Asia, where 65% and 63%, respectively, are considered as forests regenerated as a result of human activity [18]. In particular, the Congo Basin is experiencing pressure on the forests mainly due to its use by local populations for agriculture. With one exception in Gabon, where selective logging causes more damage than in other countries [27]. The other two tropical basins are experiencing more industrial forest exploitation, leading to deforestation, with palm plantations in Southeast Asia and cattle grazing facilities in South America [137,138]. Although an increase in the number of studies has been noted for Central Africa, from 2013 onwards, with an average of 1.9 papers per year instead of 0.4 before, knowledge about the degradation of the Congo Basin remains too low, as do other environmental and social areas [138].

4.2. Indicators of Composition, Structure and Regeneration Measured with Remote Sensing

In order to measure forest degradation in terms of its resilience, indicators of composition and structure make it possible to assess the state of the forest at time t . Regeneration indicators provide information about the capacity of the forest to recover by itself [37]. This study showed which indicators are usually measured in tropical rainforests, using remote sensing tools. Looking at forest composition, it is not widely studied with only one study in Borneo able to detect trait differences between pioneer and climax guilds using Landsat data [98]. In the literature [139], the results in detecting forest composition or

its specific diversity vary according to the spatial and spectral resolution of data used [98,140]. The results can be bad to medium or good if multispectral [140] or hyperspectral [141,142] images, respectively, are used. Recently, in South America, studies using very high-resolution images acquired by UAVs show the potential of this tool to study the composition of tropical moist forests (RGB images [143], hyperspectral data [144]).

The main indicators measured by remote sensing in forest degradation studies are related to forest structure. Fragmentation and canopy gaps represent two different levels in the process of degradation. Canopy gaps are isolated disturbances that occur punctually in time, in the case of selective logging for example [145]. The presence of canopy gaps does not necessarily mean that the forest is degraded according to their size, number and frequency [73,146]. This process, called “gap dynamics” [147], occurs naturally in the forest dynamic cycle, during windfalls for example. Fragmentation, on the other hand, is the result of a longer process which persists over time [58,148], which is associated with deforestation and leads to other disturbance such as forest fires [149]. Canopy gaps can therefore be considered as punctual disturbances occurring before the tipping point, which if intensified or repeated over time, can lead to forest fragmentation. When the forest is fragmented, it has gone beyond the tipping point, has reached “degraded” status, and depending on the degree of fragmentation, is approaching deforestation. Biomass is another indicator of structure measured by remote sensing. Although it cannot be accurately measured to a large extent at present, it is an integrative parameter of the forest since it depends on height, tree diameter and wood density [86]. It can also be spatialized from other structural indicators, such as canopy gaps and canopy height [62]. Besides being a good degradation indicator, quantifying vegetation biomass enables the quantification of the amount of carbon stored by vegetation. In the context of global warming, this information can be used to calculate the carbon sequestration potential of forests under future climate and land use scenarios. Nowadays carbon in forests cannot be spatialized at a large scale. However, GEDI (launched in 2018 with data that should be released to the public in late fall 2019) satellite is collecting LiDAR data, while BIOMASS (launch in 2022) will collect radar data in P-band. Both will open new opportunities in forest monitoring.

In tropical moist forests, regeneration is poorly measured using remote sensing techniques. The age of the forest and the area covered by secondary forests, while constituting a first step in the characterization of regeneration, are not sufficient on their own. Indeed, being able to link the age as well as the successional stage of a forest with its structure, as recently done in Brazil [89], is essential, as well as characterizing the composition of regenerating trees [150]. Looking at other forests, LiDAR shows good results, for example, in undergrowth vegetation cover prediction [151]. UAV-imageries seem to be a potential niche for quickly, accurately, and reliably providing highly detailed spatial, spectral, and structural information on forest regeneration [152]. In addition to characterizing regeneration itself and when time series data are available, the main trajectory of a forest can be defined by looking at its state before and after disturbance as well as years following disturbance [81,84,93].

4.3. Remote Sensing Metrics and Indices Used to Detect Tropical Moist Forest Degradation

This study leads to the same conclusions as previous reviews on the subject [49,50]. Airborne LiDAR data add value to the quantification of degradation but are not available over large territories, to a large extent and at a high temporal frequency. Moreover, it is a costly tool for local actors. Optical and radar satellite data are more affordable and regularly available. High-resolution optical data can detect canopy gaps up to a certain size [79,80], especially when working at sub-pixel scale (Table 3) or with multitemporal data. They can help to measure biomass [88] and species composition [98]. However, image resolution limits the accuracy of the results. Very high-resolution optical data provide better results and opportunities for forest monitoring. They allow the detection of small disturbances (SPOT, WorldView-2, GeoEye-1) [75,153], the boundaries of tree crown on which the biomass depends (SPOT, WorldView-2) [90,154,155], the identification of tree species (WorldView-3) [156,157] or the

measurement of biomass in combination with airborne LiDAR measurements (Planet Dove) [158,159]. These data are, however, not free of charge and are still dependent on the very numerous clouds in tropical regions, preventing regular monitoring via satellite data. Texture indices which process several pixels at a time allow to contextualize the information [104,105] and are complementary to widely used spectral indices. Using radar data and polarimetric indices can provide information about forest structure. Good results are obtained in monitoring degradation by mixing radar and optical data [92], although radar data are saturated in tropical moist forests with high biomass.

Data acquired by UAVs offer perspectives by providing both information about the structure of the forest (DSM) and about its spectral signature (at least very high-resolution RGB data) at rather low costs. Studies carried out in tropical forests show that this technology can be used to estimate biomass (Sumatra [97], Ecuador [160]), to detect changes in structure (Myanmar [93]), to monitor forest regeneration (Brazil [53], Costa Rica [161]), to characterize composition (Panama [143], Brazil [144]), to detect invasive plants (Hawaii [162]) or liana infestation (Malaysia [163]) and to locate emerging trees (Sumatra [164]). Other studies should be carried out in tropical moist forests to confirm this potential but also to test the contribution of UAVs to the measurement of forest attributes, currently requiring the installation of inventory plots, such as Lorey's height, root mean square diameter, basal area, volume and number of stems per hectare (China [165], Canada [166]). Moreover, "UAS-mounted sensors offer an extraordinary opportunity to bridge the existing gap between field observations and traditional air- and space-borne remote sensing, by providing high spatial detail over relatively large areas in an entirely new capacity for enhanced temporal retrieval"[167]. Beyond its use by scientists, the UAV which is more accessible financially [167] and easy to use, can be taken in hand by local communities and stakeholders (CBFM: Community-Based Forest Monitoring [51], CREMA: Community Resource Management Area [138]), making it possible to acquire data at a high temporal frequency and to participate in forest monitoring [52]. This tool is a good way to help local populations manage their forests and to promote the implementation of UN sustainable development goals, which must be implemented at different scales in order to be reached [29].

When the forest cover is dense, it is not always possible to produce a DTM by filtering the photogrammetric point cloud [97,168]. Sufficiently large, numerous and well-distributed canopy gaps over the study area, in which soil is visible, are required. These conditions are difficult to reach in tropical moist forests where the forest cover is dense. Other methods must then be considered in order to obtain altimetric data to normalize the DSMs produced, such as the interpolation of GPS altimeter points taken in the field [53], the use of topographic indices (TPI) [97] or the use of a DTM derived from other data such as the SRTM [77,94], which are less accurate. Ideally, methods that do not require DTMs should be established [161]. Finally, UAV technology is evolving quickly and shows good potential even though the spatial extent that can be covered remains limited compared to satellite data [169]. An interesting lead would be to evaluate how UAV data can be linked to satellite data to cover a larger spatial extent, as has been performed in temperate [170] and boreal [171] forests.

5. Conclusions

There are today multiple ways to define forest degradation leading to many interpretations. Using the concept of resilience to study forest degradation creates many opportunities and isolates the definition from any preconceived ideas. Especially, degradation criteria (i.e., composition, structure, regeneration) should be monitored. Using remote sensing seems to be a must in rainforests, which are difficult to access and cover large areas. However, tropical moist forest degradation is today poorly studied, especially in the Congo Basin which is experiencing significant pressure on its forests from the agricultural activity of local populations.

Structure is the most measured criteria by remote sensing. Fragmentation, which is an advanced stage of degradation, is now well monitored using high-resolution satellite data. Accurate measurement of canopy gaps and biomass requires LiDAR or very high-resolution data. As tropical moist forests are complex and contain lots of diversity, composition is poorly measured with the quality of measurement

linked to data resolution and the use of hyperspectral data. Finally, regeneration is not yet well characterized using remote sensing tools.

This study shows the large panel of indices (spectral, textural, polarimetric) used to measure tropical moist forest degradation. A lot of data are now available and mixing different types (LiDAR or radar and optical data) leads to good results. Very high-resolution satellites provide precious information for forest monitoring. Performant satellites giving accurate information on tropical moist forest structure are missing but the gap should soon be filled by the awaited GEDI and BIOMASS data. LiDAR and UAVs form a good bridge between field and satellite data. While the performance of the LiDAR is no longer to be demonstrated, of particular interest should be the UAV which has great potential and would be easily used by local communities and stakeholders.

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