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# **Towards rapid assessments of tree species diversity and structure in fragmented tropical forests: A review of perspectives offered by remotely-sensed and field-based data**

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## **Abstract**

With forest fragmentation continuing in many parts of the tropics, it is likely that fragmented forests will become the rule for most remaining global tropical forests in the next decades. In this context, there is a need for practical tools to assess and monitor fragmented forests if we are to conserve tree species diversity as much as possible. Several methods, either using (1) field-based or (2) remote-sensing approaches could be used to achieve this goal. This paper aims at providing a state-of-the-art review of both approaches in order to make recommendations for rapid and cost-effective assessments of tree species diversity and forest structure, with specific applications in studies of fragmented tropical forests. Overall both methods have pros and cons, depending on the type of data needed to address the research objectives and the quantity of resources available. We suggest combining the use of both field-based and remotely-sensed methods as they can be complementary. Remote-sensing data should be used to predict and map the tree species diversity and stand structure at regional scales, while field-inventories provide accurate information at local scales and allow validation of remotely-sensed data. For field-inventories, we recommend the use of small (e.g. 20 × 50 m) plots with a 10 cm DBH minimum measurement. In terms of remotely-sensed techniques, if funding is sufficient, airborne imagery seems the best regarding the quality of information (i.e. hyperspectral and hyperspatial imagery, LiDAR). If funding is limited, a cost-effective alternative providing reasonably accurate estimates would be the use of high-resolution satellite imagery such as Worldview. Ultimately, for studies where data accessible for free is the only possible option, we recommend the use of Sentinel-2, although it is relatively coarser in terms of quality. However, further research needs to be done to validate these approaches in fragmented tropical forests.

**Keywords** : Airborne imagery; Biodiversity; Forest fragmentation; Forest inventory; Satellite imagery; Tree species richness.

## **1. Introduction**

Tropical rainforests are recognized for hosting a significant proportion of global biodiversity (Gaston 2000; Myers et al. 2000) and their conservation constitutes a major challenge (Koh and Sodhi 2010). Over the last five decades, increases in logging, agriculture and urban growth have led to significant losses of tropical forest (Houghton 1994; Lewis et al. 2015; Rosa et al. 2016) resulting in unprecedented fragmentation of this habitat (Laurance and Bierregaard 1997; Groombridge and Jenkins 2000; Koh and Wilcove 2008; Peres et al. 2010). A recent study revealed that 70% of remaining global forests are within 1 km of the forest's edge, subject to the degrading effects of fragmentation (Haddad et al. 2015). Global patterns of tropical forest fragmentation predict large increases in the total number of forest remnants in the future (by a factor of up to 33 over the next 50 years), as well as a decrease in their size (Taubert et al. 2018). With fragmentation continuing in many parts of the tropics, fragmentation might become the rule for most of the remaining global tropical forests in the next decades. Alroy (2017) reported that habitat disturbances have already led to a loss of about 30% of tree species in tropical forests. In this context, tropical forests urgently need to be monitored and closely managed if we are to conserve tree species diversity as much as possible.

Besides the direct loss of diversity caused by habitat reduction, fragmentation affects tree communities through impacts of edge-effects on the remaining fragments and increases in isolation which limits connections between them (see Fahrig 2003; Harper et al. 2005; Ewers and Didham 2006; Laurance 2008; Heinken and Weber 2013). In addition, because forest remnants are more accessible than continuous forests, after fragmentation, they are often exposed to human-induced disturbances such as illegal timber harvesting and land-clearance by small-scale farmers (Hamer et al. 1997; Fahrig 2003). Finally, due to their long lifespans, tree species are affected by fragmentation through slow long-term processes that lead to time-delayed species extinctions (Helm et al. 2006; Vellend et al. 2006; Metzger et al. 2009; Krauss et al. 2010); a process known as "extinction debt" (Tilman et al. 1994). All these factors combined together make it very difficult to estimate the real impact of fragmentation on tree communities over long time periods.

As noted by Kangas and Maltamo (2006), "All decision-making requires information. In forestry, this information is acquired by means of forest inventories, systems for measuring the extent, quantity and condition of forests." In this context, forest managers, as well as policy makers, have a need for practical forest inventory

tools to assess and to monitor trends for biodiversity in fragmented tropical forests, thus providing information in support of management or intervention plans. While criteria and indicators for fragmented tropical forests may vary according to policy objectives (e.g. sustainable timber harvesting, carbon sequestration, maintenance of biodiversity at an ecosystem or landscape level, conservation of rare, endangered or valuable species), all are underpinned by information gained from forest inventories.

Although substantial efforts have been made by researchers over the last decades, the composition and structure of large areas of tropical forests remain poorly studied (Foster et al. 1998; Feeley and Silman 2011), thereby making forest management decisions difficult in many countries. This is even more relevant in fragmented tropical forests, considering that while most ecological studies have focused on undisturbed tropical forests, research has also highlighted possible conservation values of disturbed or fragmented tropical forests (e.g. Turner and Corlett 1996; Baynes et al. 2016). In classical field-based methods, much of the time and resources necessary to inventory sites are used for travel, which makes time spent in the field extremely valuable (Baraloto et al. 2012). Thus, a rapid inventory method providing information on both biodiversity (i.e. number of species) and forest structure would represent a major tool to improve our ability to plan for management and conservation of fragmented forests. Along with several methods using field-based approaches, the last decades have also seen increasing development of technologies using remote-sensing that could be used to achieve this goal.

Many studies have been published regarding rapid assessment of tree species diversity and forest structure based on field inventories (e.g. Higgins et al. 2004; Jayakumar et al. 2011; Baraloto et al. 2012; Arellano et al. 2016). Although several studies and reviews also exist about the potential of remote-sensing for forest inventories (e.g. Nagendra 2001; Chambers et al. 2007; Gillespie et al. 2008; Fassnacht et al. 2016; Lausch et al. 2016), only a few have addressed an overview of these technologies for assessments of both taxonomic and structural diversity at the same time (Lausch et al. 2016; Mulatu et al. 2017). In addition, to our knowledge very few studies have properly reviewed and compared the possibilities offered by field-based and remotely-sensed approaches at the same time (e.g. Bustamante et al. 2016). Even though this was attempted by Jayakumar et al. (2011), when this review was published they concluded that remote-sensing technologies needed more development and research. More importantly, while these studies were focused on undisturbed forests, to our knowledge no study has addressed what is best suited to highly-disturbed fragmented forests. In that context, this paper aims at providing a state-of-the-art review of both field-based and remotely-sensed approaches in order to make recommendations for rapid and cost-effective assessments of tree species diversity and forest structure, with specific applications in studies of fragmented tropical forests.

Studies in fragmented tropical forests have several requirements. Forest fragmentation has usually been described as a non-random process and the configuration and shape of remaining fragments are often influenced by environmental factors such as soil type, topography or wetness (Turner 1989; Laurance 2008; Ibanez et al. 2017). Therefore, most forest remnants present a high variability of sizes and shapes, especially over regional scales (Ranta et al. 1998; Hill and Curran 2003; Ibanez et al. 2017), which is a problem for both field-based and remotely-sensed techniques. In contrast, most studies in contiguous tropical forests do not have to deal with this type of problem and, for example, allow implementation of very large survey plots of up to 50 ha (e.g. Lee et al. 2002). Recently, Taubert et al. (2018) reported that varying patterns of local deforestation (assessed from global data on forest cover) produced intriguingly similar patterns of tropical forest fragmentation at the continental scale. In this study, mean (median) sizes of global tropical forest fragments were 17, 13 and 13 ha for the Americas, Africa and Asia-Australia respectively, and are expected to decrease in future (Taubert et al. 2018). Forest fragments also presented very similar fractal dimension and perimeter scaling in the three continents. In their study at a landscape scale, even smaller fragment sizes were reported by Ibanez et al. (2017). Forest fragments presented irregular shapes and had sizes ranging from 0.1 to 54.6 ha with a median size of only 1.6 ha. Assessment techniques should thus also be able to deal with such small sizes of forest fragments.

Finally, another important requirement is the geographic area covered by an assessment. Although the geographic area of a study usually depends on both research objectives and resource availability, fragmented landscapes could theoretically be studied on scales from a few thousand hectares (e.g. Baynes et al. 2016; Ibanez et al. 2017) up to the total of tropical forest areas at the continental scale (940, 577 and 391 Mha for Americas, Africa and Asia-Australia respectively (Taubert et al. 2018)). Assessment methods addressing the future of fragmented tropical forests should thus deal with wide ranges in the assessment scale, and in the shape and size of fragments, while also being affordable. This is particularly important since most of this topic concerns developing countries where limited funding may only allow studies on a restricted scale.

## **2. Field-based inventory methods**

Over the last decades, studies of tree species diversity in tropical forests have been increasingly standardized in order to allow comparison among research groups (Condit 1995; Condit et al. 2002; Malhi et al. 2002; Arellano et al. 2016). Some of the field-based inventory methods commonly used have been summarized in Table 1.

Table 1 : Examples of field-based inventory methods commonly used to assess tree species diversity and structure in tropical forests worldwide. Field effort is based on calculations from Baraloto et al. (2012) and Arellano et al. (2016). \*: the five plot methods compared in the study from Baraloto et al. (2012). DBH: diameter at breast height.

Method	Shape	Area covered (ha)	Area inventoried (ha)	DBH min (cm)	Permanent	Field effort (person-days)	References
Gentry Plot*	2 × 50 m transects	2	0.1	2.5	No	7	Boyle (1996); Phillips et al. (2003a,b)
Whittaker Plot*	20 × 50 m	0.1	0.1	2.5	No	7	Campbell et al. (2002)
Modified Gentry Plot*	10 × 50 m transects	2	0.5	Variable	No	8	Baraloto et al. (2011)
0.5 ha Plot*	50 × 100 m	0.5	0.5	2.5	Yes	15	Baraloto et al. (2012)
1 ha Plot*	100 × 100 m	1	1	10	Yes	25	FAO (1981)
Circular Plot	30 m radius	0.28	0.28	10	Yes	5	Asner et al. (2010)
20-50 ha Plot	500 × 500 m to 1000 × 500 m	Up to 52	Up to 50	1	Yes	> 500	Condit (1995)
0.1 ha Plot	20 × 50 m	0.1	0.1	2.5	No	5-20	Arellano et al. (2016)

Overall, all field-based inventory methods have pros and cons and the most appropriate largely depends on (1) the quantity of resources available and (2) the type of data needed to address the research objectives. However, for specific applications in fragmented forests studies, several important aspects need to be considered. Firstly, an important decision is whether the plots need to be permanent or not. Permanent plots have considerable advantages for studies of forest dynamics and tree-species demographic rates. However, because individual trees need to be tagged and spatially located within permanently marked plots, they require a significant amount of time and effort to establish and monitor (Arellano et al. 2016). Temporary plots, on the other hand, do not require tagging and mapping of individual trees or permanent plot delineations, and each individual tree is only measured once. Since the objective in fragmented forests studies is to gather basic information on forest structure and composition over large areas, time- and cost-effective temporary plots are likely to be more suitable.

Considering the variety of methods found in the literature, including circular/square/rectangular plots or transects (see Table 1), other important aspects are both the size and the shape of the plots. Initially recommended by the Food and Agriculture Organization (FAO 1981), one of the most widespread field-based forest inventory methods is the 1-ha square plot (e.g. Phillips et al. 2009; Stropp et al. 2009). However, because of aggregative

patterns and rare species in tropical forests, recent studies have suggested this approach **is** not the most appropriate to measure species diversity (Phillips et al. 2003b). This illustrates how the area inventoried vs the area covered is important in inventories of tropical forests. In Gentry plots for example, the inventoried area is only 0.1 ha. However, because this plot method is composed by ten  $2 \times 50$  m transects randomly dispersed within 2 ha (covered area), it allows assessment of more rare species than would be allowed by contiguous plots of similar size. Recently, after contrasting five of the plot methods presented in Table 1, Baraloto et al. (2012) recommended the use of 0.5-ha modified Gentry plots for rapid inventories. Modified Gentry plots were the most efficient at providing accurate estimates (i.e. smaller coefficient of variation) of both tree diversity and above ground biomass over other methods.

On the other hand, according to Arellano et al. (2016), a problem with Gentry plots is that they are spread samples, and therefore diversity measures are affected by both alpha-diversity (local diversity recorded in a single transect) and beta-diversity on the 2-ha scale (the difference between each transect). Thus, although this method is useful for rapidly gaining a good understanding of a site's gamma-diversity, results can be unclear when looking at inter-sample comparisons to measure beta-diversity at larger scales (Anderson et al. 2011; Tuomisto 2011). For that reason, Arellano et al. (2016) recommended the use of contiguous  $20 \times 50$  m plots as standard protocol for woody plant inventories and soil characterization in tropical forests, since their installation is also relatively time- and cost-effective.

On the other hand, while recommendations of both Baraloto et al. (2012) and Arellano et al. (2016) were based on undisturbed forests; to our knowledge no published studies have addressed which plot shape is best suited to highly-disturbed fragmented forests. Two recent studies used either transects or circular plots (10 m radius) to extensively inventory trees in fragmented forests of the southern Philippines and New Caledonia respectively (Baynes et al. 2016; Ibanez et al. 2017). However, in both studies no comparison was made with other methods so we do not know if one is more time- and cost-effective than the other. Circular plots are widely regarded as difficult to demarcate in the dense understory of tropical forests (Alder and Synnott 1992), which makes them less suitable for rapid assessment of tree diversity. Only a few researchers continue to use them, mostly for calibration of remote-sensing estimates of above ground biomass or species diversity (e.g., Asner et al. 2010; Mauya et al. 2015; Schäfer et al. 2016).

Another major choice in fragmented forest studies is the size of the plot, since it needs to fit within most forest remnants in the area of interest. Considering the patchy distribution and the typically small size of forest

fragments (global mean size of about 15 ha, [Taubert et al. 2018](#)), large (20-50 ha) plots are obviously completely unsuited. In addition, the irregularity of forest fragment shapes leads to higher edge-area ratio than for fragments with smoother and more regular shapes. For example, a 4-ha fragment may be a very thin and long strip following a river corridor in which a large plot would be impossible to locate. Therefore, because the modified Gentry plots recommended by [Baraloto et al. \(2012\)](#) have a dispersed spatial arrangement within a 2-ha area, we suggest fragmented forests are more likely to present sizes and shapes unsuitable for this type of plot. The 1-ha square plots are also likely to be unsuited for the same reason and thus, if we want to cover many forest remnants, smaller size plots might be more relevant.

Apart from the need to locate plots within small and variably-shaped fragments, the other key issue relating to the choice of plot size is its relationship with inventory cost and statistical power. Smaller plots take less time to install and measure, allowing more plots to be inventoried for a given financial or resource budget. However, smaller plots have a higher between-plot variance, and this must be traded-off against the plot cost in order to identify an optimal plot size ([Evans and Viengkham 2001](#)). The optimal plot size will be one where the desired statistical power (expressed as either a desired precision of the sample mean or ability to test a hypothesis of interest) is achieved for the least overall cost. For example, [Grussu et al. \(2015\)](#) re-analysed data from existing 1-ha permanent sample plots in logged and unlogged forests in Papua New Guinea, in order to evaluate the optimal plot size for efficiently achieving estimates of tree species richness and carbon stocks. The original 1-ha plots were not found to be efficient, and optimum plot sizes for estimating tree species richness were 0.08 and 0.2 ha in unlogged and logged forests respectively. The larger optimum plot size in the logged forests was attributed to the greater within-plot variation in logged forests due to the presence of open harvesting coupes.

The last aspect to be considered in the choice of the inventory method is the minimum diameter for recording. While some methods start with a minimum diameter of 1 or 2.5 cm DBH, other methods start at 10 cm DBH (see [Table 1](#)). Small trees (from 1 to 10 cm) are of particular interest as they provide information about both tree species regeneration and species that are not likely to grow into larger size classes. [Baraloto et al. \(2012\)](#) demonstrated well how this choice of minimum diameter can influence results and that smaller minimum diameters always provide better results. In this study, the relative ratio of overall richness between communities with a minimum diameter of 10 cm vs 2.5 cm was about 80 %. Unfortunately, because resources are usually limited a trade-off must be made between the amount of information collected and its cost. Thus, a minimum

diameter of 10 cm seems more suited for time- and cost-effective assessments, allowing coverage of more forest remnants in the same amount of time.

### **3. Remotely-sensed inventory methods**

Over the last decades, remote-sensing investigations have resulted in new ecological insights for tropical forests. [Chambers et al. \(2007\)](#) categorized them in three major research areas: (1) ecosystem process and forest function, (2) forest structure and species composition, and (3) land-use and land-cover change. Our review investigates techniques used in the second of these research areas. To our knowledge, no study has used remote-sensing techniques specifically for assessment of tree species diversity and forest structure in fragmented tropical forests. Thus, most of the available techniques will be described using various examples from literature and their applicability for studies in fragmented forests will be discussed later. Techniques for assessment of (1) species composition and (2) forest structure will be presented in the next two sections.

#### 3.1 Forest species composition

Assessing biodiversity from remote-sensing data has been well-researched over the last two decades ([Nagendra 2001](#); [Turner et al. 2003](#); [Rocchini et al. 2010](#); [Nagendra et al. 2013](#); [Kuenzer et al. 2014](#); [Pettorelli et al. 2014](#); [Asner 2015](#)). Three general approaches have been distinguished for assessment of species diversity and distribution using remote-sensing data ([Nagendra 2001](#); [Kerr and Ostrovsky 2003](#); [Strand et al. 2007](#); [Lausch et al. 2016](#)): (1) habitat or ecosystem mapping, (2) direct mapping of individual plants and species, and (3) modeling of relationships between remotely-sensed data and species diversity and distribution patterns. Earlier studies mainly used high-resolution aerial photographs to identify vegetation classes such as forest type or individual plants to the species level ([Gillespie et al. 2008](#)). Recent research has focused on the use of airborne or satellite imagery at different spatial and spectral resolutions. Examples of remote-sensing techniques recently used for assessment of species composition have been summarized in [Table 2](#).

Habitat or ecosystems mapping is usually based on medium resolution multispectral data from satellite imagery such as Terra-ASTER, Landsat-TM/ETM+ or Sentinel-2 ([Nagendra et al. 2013](#); [Kuenzer et al. 2014](#); [Corbane et al. 2015](#)). Such imagery can also be used for predicting species diversity by extracting measures of spectral entropy ([Gillespie et al. 2009](#); [Hernández-Stefanoni and Dupuy 2007](#); [Rocchini et al. 2010](#); [Hernández-Stefanoni et al. 2011](#); [Maeda et al. 2014](#)). Mapping of individual plants (i.e. tree species identification) on the other hand, is regarded as needing higher spatial and spectral resolutions than those offered by medium resolution satellite data

(Turner et al. 2003; Gillespie et al. 2008). With medium resolutions of a few tens of meters, a single pixel often encompasses numerous individual trees, sometimes even crossing habitat boundaries (Small 2004; Nagendra and Rocchini 2008). With each pixel corresponding to a mixed field signature averaged across several objects, this necessarily leads to losses of information about species diversity and forest structure.

Table 2 : Examples of remote-sensing methods used for assessment of plant species diversity sorted in increasing order of spatial resolution. Costs for satellite imagery can be found in <http://www.landinfo.com>. Exact costs for airborne methods depend on the sampling area: larger-area projects are more cost-effective than those in small areas. For example, [Asner et al. \(2010\)](#) reported a cost of less than 0.08USD/ha for a 4.3 million ha analysis using the CAO LiDAR. PAN = panchromatic band. UAS = unmanned aerial systems.

Types	Spatial resolution	No of bands	Sensors	Spectral resolution (nm)	Costs	Examples of use	References
Satellite	30 m (15 m PAN band)	9	Landsat (TM, ETM+)	435-1384	Free	Modeling diversity in a tropical forest	<a href="#">Hernández-Stefanoni et al. (2012)</a>
						Assessing tree species diversity in temperate forest	<a href="#">Arekhi et al. (2017)</a>
Satellite	10 m (4 bands) 20 m (7 bands) 60 m (2 bands)	13	Sentinel-2	443-2190	Free	Crop and tree species classification in central Europe	<a href="#">Immitzer et al. (2016)</a>
						Discrimination of tropical forest types, dominant species and functional guilds	<a href="#">Laurin et al. (2016)</a>
Satellite	4 m (1 m PAN band)	5	IKONOS	450-900	Medium (10 USD/km <sup>2</sup> )	Mapping invasive wetland species in Hudson River	<a href="#">Laba et al. (2010)</a>
Airborne	3.3-3.6 m	224	AVIRIS Spectrometer	366-2510	High	Hyperspectral remote-sensing of canopy biodiversity in Hawaiian lowland rainforests	<a href="#">Carlson et al. (2007)</a>
Satellite	2.8 m (0.6 m PAN band)	5	Quickbird	450-900	Medium (17.5 USD/km <sup>2</sup> )	Detection of invasive species in southwest Texas	<a href="#">Everitt et al. (2005)</a>
Satellite	2 m	8	WorldView	400-1040	Medium (17.5 USD/km <sup>2</sup> )	Detection of invasive species in Australia	<a href="#">Robinson et al. (2016)</a>
						Tree species classification in temperate Austrian forest	<a href="#">Immitzer et al. (2012)</a>

						Tree species mapping in humid subtropical forest	Cho et al. (2015)
Satellite	2 m (0.5 m PAN band)	5	GeoEye	450-920	Medium (17.5 USD/km <sup>2</sup> )	Assessment of population structure of <i>Acacia tortilis</i>	van Coillie et al. (2016)
Airborne	2 m	114	Goddard's LiDAR + Hyperspectral (G-LiHT) imager	407-1007	Free. Cover limited to some parts of the USA	Mapping plant richness in a forest landscape	Hakkenberg et al. (2018)
Airborne	1.12 m	72	CAO-Alpha HiFIS spectrometer + LiDAR	367-1058	High	Mapping tree species composition in savannas	Cho et al. (2012)
						Tree species mapping in Panama tropical forest	Baldeck et al. (2015)
Airborne	1 m	129	AisaEAGLE imaging spectrometer	400-1000	High	Mapping tree species diversity of tropical forest	Schäfer et al. (2016)
UAS	0.05 m	1 (RGB)	Photograph camera	450-690	Low (< 2000 USD)	Identification of tropical Ecuadorian trees	Peck et al. (2012)
						Mapping tropical forest diversity using a drone	Koh and Wich (2012)
						Classification of riparian forest species	Michez et al. (2016)

Hyperspatial (i.e. high spatial resolution) satellite (e.g. IKONOS, Quickbird, Worldview-2) or aerial imagery seem better suited for biodiversity mapping as a pixel resolution of only a few meters corresponds well to the size of individual tree crowns (Read et al. 2003; Wulder et al. 2004). Yet, it has also been argued that while hyperspatial data are well suited to locating features within an image, they might be less suited for species identification (Nagendra and Rocchini 2008; Nagendra et al. 2010). At high resolution, problems arise from increases in variability of signatures among pixels covering the same individual tree (Avena et al. 1999; Song and Woodcock 2002; Rocchini and Vannini 2010). This can happen for instance when pixels are smaller than tree crowns and cover different parts such as bark, sunlit leaves, shaded leaves and even sometimes forest floor (Gougeon 1995; Meyera et al. 1996). However, more recently, Baldeck et al. (2015) argued that within-crown spectral variability does not prevent species classification of pixels and that hyperspatial data are suitable for both accurate feature location and species identification. They hypothesized that this disparity could be caused by recent developments in classification methods, with latter methods able to accommodate complex within-class variations.

Hyperspectral (i.e. high spectral resolution) imagery, on the other hand, is an even more important tool for tree species identification, reducing the need for extremely high spatial resolutions (and its possible corresponding noise) as it allows recording of spectral signatures down to sub-pixel levels (He et al. 2011). Using a series of contiguous bands covering narrow spectral ranges, it is possible to record information related to a range of plant properties such as water content, leaf pigment and chemical composition (Curran 1989; Martin and Aber 1997; Townsend et al. 2008). Recent studies in tropical forests in Sarawak (Asner et al. 2012a), Amazonia (Asner and Martin 2011), Hawaii (Asner and Martin 2009), and Australia (Asner et al. 2009) have shown that, based on their structural and biochemical properties, tree species often have unique spectral signatures. Variability in hyperspectral information can thus be used for discriminating tree species at a landscape scale, even in complex ecosystems such as tropical forests (Cochrane 2000; Clark et al. 2005). Nowadays, both aerial and satellite sensors enable detection of subtle differences in reflectance among species which has led to advancements in tree species identification (Clark and Roberts 2012; Laurin et al. 2014).

So far, most studies using high-resolution imagery to identify individual tree species come from areas which have only a few dominant species, such as temperate/boreal forests (e.g. Immitzer et al. 2012), savannas (e.g. Colgan et al. 2012) or mangroves (e.g. Wang et al. 2004). Although already challenging when there are a few species, this task presents even greater challenges in tropical forests where the species richness of trees > 10 cm in diameter may exceed 300 species per ha (Valencia et al. 1994), along with higher canopy complexity and

frequent cloud cover. The mapping of individual tree species is usually based on a supervised classification that requires spectral training and validation data on each target species (e.g. [Baldeck and Asner 2013](#)). However, considering the high variety of tree species in tropical forests, with many of them rare (especially in fragmented forests), training and validation data would be practically impossible to obtain for each species. Instead, [Baldeck et al. \(2015\)](#) used single-class classification methods to identify individuals of three focal canopy species amongst a diverse tropical forest on Barro Colorado Island. Nevertheless, although efficient due to the low amount of training data required, these methods only allow a focus on a limited number of species, which make them unsuitable for assessment of species diversity in fragmented tropical forests.

An alternative for mapping species diversity would be the use of unsupervised classification as it does not require any prior information on the species. The main idea of this approach is not to directly relate spectral species to biological species, but rather to approximate the diversity of species observed in the field from the spectral species distribution ([Carlson et al. 2007](#); [Asner and Martin 2011](#); [Féret and Asner 2014](#)). According to the spectral variation hypothesis (SVH) ([Palmer et al. 2002](#)), the spectral variation of a site can be related to its ecosystem heterogeneity. Since greater heterogeneity allows a higher number of species to coexist ([Huggett 1995](#); [Wilson 2000](#)), this hypothesis has potential predictive power for species diversity ([Rocchini 2007](#); [Oldeland et al. 2010](#); [Rocchini et al. 2010](#)). This reasoning has particularly been used by studies that aimed at predicting species diversity based on medium resolution satellite imagery (e.g. [Rocchini et al. 2010](#); [Hernández-Stefanoni et al. 2011](#); [Maeda et al. 2014](#)). The mapping of species diversity based on unsupervised classification might have similarities with the SVH as the clustering result can be interpreted as a measure of spectral heterogeneity ([Medina et al. 2013](#); [Féret and Asner 2014](#)). However, while the SVH suggests that spectral variation arises from heterogeneity of habitats, when using high spatial resolution imagery, spectral variation is assumed to arise from heterogeneity in canopy-level tree species composition ([Féret and Asner 2014](#)).

Although unsupervised classification has potential for direct prediction of tree species diversity from high-resolution imaging spectroscopy data, so far very few studies have attempted to apply this approach. In their study, [Baldeck and Asner \(2013\)](#) and [Féret and Asner \(2014\)](#) suggested methods using pixel-based classification results. More recently, [Schäfer et al. \(2016\)](#) developed a method using object-based (i.e. crown-based) classification. Earlier studies have used transformation of individual tree crown delineations (from remotely-sensed imagery) into objects in order to improve species discrimination ([Lucas et al. 2008](#); [Féret and Asner 2012](#)). This approach has the advantage that reflectance characteristics are averaged over entire tree crowns, which decreases within-species spectral variation ([Blaschke et al. 2014](#)). However, despite the relatively good

estimates of species richness provided by this approach ( $R^2 = 0.5$  in Schäfer et al. (2016)), they focused on small areas (around 100 ha). We suggest that individual tree crown delineation could be more difficult to apply to larger areas such those used in fragmented forest studies. For studies at landscape or regional scales, pixel-based classification, although being not as accurate, might be easier to implement.

Another promising candidate to improve tree biodiversity mapping is the combination of hyperspectral and light detection and ranging (LiDAR) remote-sensing (Dalponte et al. 2008; Holmgren et al. 2008; Jones et al. 2010; Dinuls et al. 2012; Féret and Asner 2012; Leutner et al. 2012; Ghosh et al. 2014). It is expected that hyperspectral imagery coupled with LiDAR data may complement each other and improve species discrimination by detection of more subtle species-specific spectral and structural properties (Féret and Asner 2012). While hyperspectral data provides detailed surface reflectance characteristics related to leaf chemistry, LiDAR provides detailed three-dimensional positional information related to foliage density and crown architecture (Leutner et al. 2012). However, despite the promising possibilities offered by this approach, to date few studies have used it as the method is relatively recent.

Finally, the last decade has seen increasing development of innovative technologies using unmanned aerial systems (UAS). These new technologies have been described as an effective alternative for cost-effective assessments of forest biodiversity using very high spatial ( $< 0.1$  m) and temporal resolution (Koh and Wich 2012). Several studies have taken advantages of these two characteristics in a broad range of forest topics such as tree and forest characterization (Lisein et al. 2013; Zarco-Tejada et al. 2014), forest species composition (Dunford et al. 2009; Peck et al. 2012; Gini et al. 2014; Michez et al. 2016) and forest biodiversity assessment (Getzin et al. 2012). References on assessment of tree species biodiversity using UAS imagery are still rare in the literature and concern mostly temperate regions (e.g. Getzin et al. 2012). Moreover, while most of the recent studies from aerial or satellite imagery used hyperspectral data for tree species identification, most studies based on UAS only used hyperspatial data from high-resolution photograph cameras. However, nowadays even spectral camera systems (e.g. Saari et al. 2011; Hruska et al. 2012; Zarco-Tejada et al. 2013; Franklin et al. 2017), as well as LiDAR systems (e.g. Lin et al. 2011; Wallace et al. 2012), may be mounted on UAS to obtain both hyperspectral imagery and three-dimensional forest scans. Although to our knowledge no study has used this low-cost approach in highly diverse tropical forests so far, it constitutes a promising candidate method for future studies on tree diversity, especially in developing countries where satellite and airborne sensors can be prohibitively costly and inaccessible for researchers.

### 3.2 Forest structure

Assessing forest stand structure from remote-sensing data has also been well-researched for several decades (Næsset 2002; Clark et al. 2011; Hou et al. 2011; Wulder et al. 2012; Henry et al. 2015; Lu et al. 2016). It can be categorized into three different approaches, all related to each other: (1) detecting and quantifying forest aboveground biomass (AGB), (2) assessing vertical vegetation structure and structural complexity, and (3) predicting horizontal forest structural stand parameters (e.g. mean diameter, basal area, stem density). Table 3 summarizes examples of remotely-sensed techniques recently used in the context of these three approaches.

Over the last decades, studies using remote-sensing technologies to assess forest structure have mostly focused on quantification of AGB in relation to the monitoring of global carbon fluxes. Medium spatial resolution data from satellite imagery, such as Landsat-TM, have been the most widely used remotely-sensed systems for biomass estimations (Main-Knorn et al. 2013; Latifi et al. 2015; Lausch et al. 2016) as they provide good compromises regarding data-availability, data-processing and detail level. Broadband indices derived from such imagery, such as the Normalized Difference Vegetation Index (NDVI), have been used for a long time in tropical forest studies as a correlate with biomass (Sader et al. 1989; Steininger 2000; Foody et al. 2003).

Table 3 : Examples of remote-sensing methods used for assessment of forest structure sorted in increasing order of spatial resolution. Costs for satellite imagery can be found in <http://www.landinfo.com>. Exact costs for airborne methods depend on the sampling area: larger-area projects are more cost-effective than those in small-areas. PAN = panchromatic band. UAS = unmanned aerial system.

Types	Spatial resolution	No of bands	Sensors	Spectral resolution (nm)	Costs	Examples of use	References
Satellite	30 m (15 m PAN band)	9	Landsat (TM, ETM+)	435-1384	Free	Modeling biomass in Brazil Atlantic forest	<a href="#">Barbosa et al. (2014)</a>
						Mapping carbon stock in the Amazon	<a href="#">Asner et al. (2010)</a>
Airborne	5 m	-	CAO-Alpha LiDAR	-	High	Tropical forest carbon mapping	<a href="#">Asner et al. (2012b)</a>
Satellite	4 m (1 m PAN band)	5	IKONOS	450-900	Medium (10 USD/km <sup>2</sup> )	Estimating canopy structure in an Amazon forest	<a href="#">Asner et al. (2002)</a>
						Landscape and regional variations in tropical forest canopy structure	<a href="#">Malhi and Román-Cuesta (2008)</a>
Satellite	2.8 m (0.6 m PAN band)	5	Quickbird	450-900	Medium (17.5 USD/km <sup>2</sup> )	Mapping aboveground biomass of African forest mosaics	<a href="#">Bastin et al. (2014)</a>
Satellite	2 m (0.5 m PAN band)	5	GeoEye	450-920	Medium (17.5 USD/km <sup>2</sup> )		
Satellite	2 m (0.5 m PAN band)	5	Pléiades	430-950	Medium (12.5 USD/km <sup>2</sup> )	Prediction of forest structure in New Caledonia	<a href="#">Blanchard et al. (2015)</a>
Satellite	2 m	1 (RGB)	Google Earth image	450-690	Free	Assessing aboveground tropical forest biomass	<a href="#">Ploton et al. (2012)</a>
Airborne	2 m	480	CAO-AToMS (spectrometer + LiDAR)	252-2648	High	Landscape-scale changes in forest structure	<a href="#">Asner et al. (2014)</a>
Airborne	1.6 m	210	FLI-MAP LiDAR +	400-2500	High	Estimation of tropical rainforest aboveground	<a href="#">Clark et al. (2011)</a>

			HYDUCE spectrometer			biomass	
Airborne	1 m	1 (RGB)	Photograph camera	450-690	High	Predicting tropical forest stand structure	Couteron et al. (2005)
UAS	0.05 m	1 (RGB)	Photograph camera	450-690	Low (< 2000 USD)	Forest structure estimation in temperate coniferous forest	Ota et al. (2017)
						Biomass estimation in a tropical woodland	Kachamba et al. (2016)

Laser scanning methods such as LiDAR have also emerged as a promising technology for estimating forest height, volume and AGB in boreal, temperate and tropical forests (Drake et al. 2002; Lefsky et al. 2002a; Clark et al. 2004; Hyyppä et al. 2008). Able to provide direct descriptors of forest structure including tree height, crown size, and tree density (Heurich and Thoma 2008; Bergen et al. 2009), LiDAR sensors are of particular interest for the estimation of forest biomass and carbon stocks (Corona and Fattorini 2008; Steinmann et al. 2013). Spaceborne systems, such as the Geoscience Laser Altimeter System (GLAS) sensor or the Global Ecosystem Dynamics Investigation (GEDI) sensor (scheduled for launch in 2018 on the International Space Station, Stavros et al. 2017), usually provide large foot-print LiDAR data (i.e. 1-80 m) (Lefsky et al. 2002b; Lefsky et al. 2007). In contrast, airborne systems are able to provide LiDAR data down to a very small foot-print (i.e. 0.25-0.60 m) (Lefsky et al. 2002b). It is also expected that LiDAR data coupled with hyperspectral imagery may complement each other and improve estimates of biomass and other forest structure properties, especially if hyperspectral imagery provides canopy species, phenology and biochemical information (Asner et al. 2007; Koetz et al., 2007; Asner et al. 2008). The most recent methodological improvements for estimation of AGB involve remote-sensing data at a high spatial resolution such those provided by satellites (e.g. Pléiades, World View, IKONOS, Quickbird) (Bastin et al. 2014) or aerial photographs (Kachamba et al. 2016). Ploton et al. (2012) even used free high-resolution images from Google Earth to assess AGB.

Numerous modeling approaches have been proposed in order to convert the physical signal (i.e. canopy texture or LiDAR waveform) into forest structural parameters such as AGB (Asner et al. 2012b; Barbier et al. 2012; Vincent et al. 2014). The underlying theory of these approaches is that, considering the relationship between tree height and tree diameter (Feldpausch et al. 2010), trees visible in the canopy usually constitute most of the AGB of tropical forests (Clark et al. 2001; Rutishauser et al. 2010; Slik et al. 2013). Forest structure could thus be directly predicted from the physical signal observed from the sky. While LiDAR-derived AGB estimates are usually based on forest height metrics (e.g. Asner et al. 2010; Saatchi et al. 2011, Baccini et al. 2012), those based on approaches using canopy texture from high resolution imagery come from the horizontal distribution of crown sizes in the canopy (Bastin et al. 2014). For example, several studies report that high AGB was related to stands exhibiting coarser canopy texture on high-resolution imagery (Proisy et al. 2007; Ploton et al. 2012; Blanchard et al. 2015).

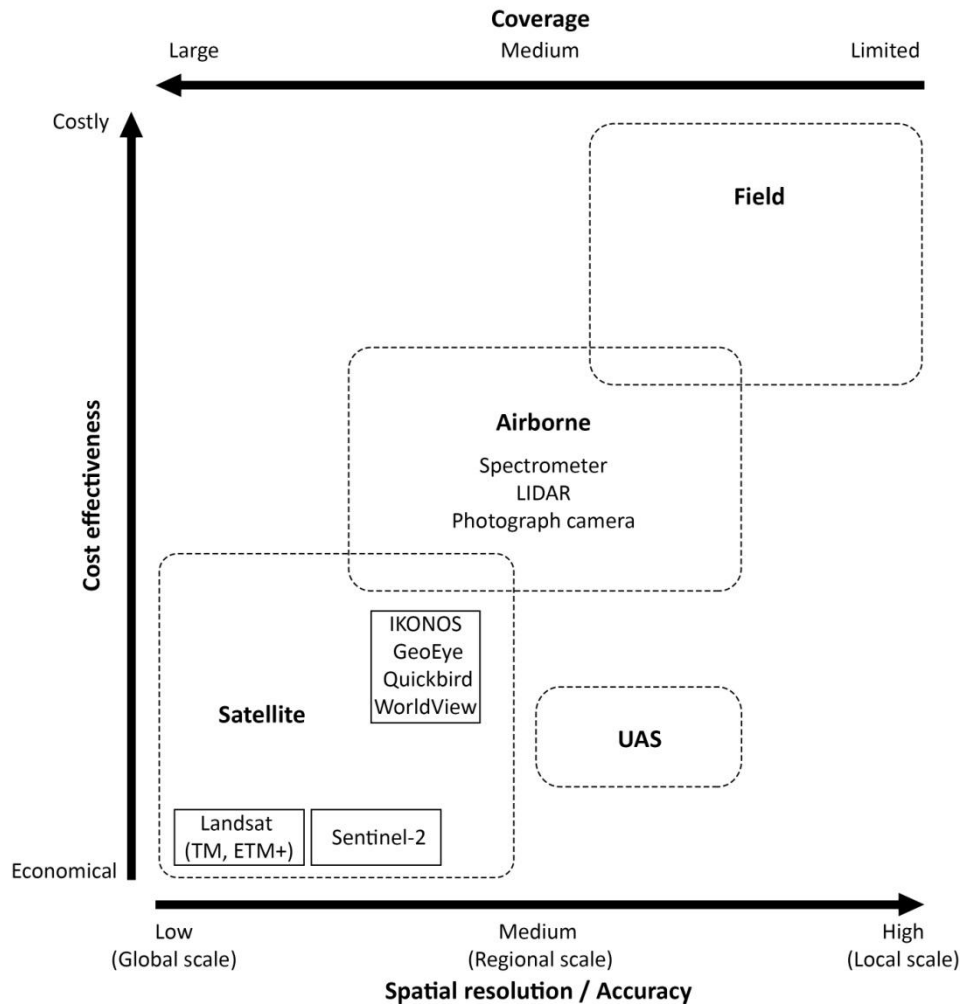
Despite the importance of mapping AGB (i.e. carbon stocks), studies of fragmented tropical forest also need information on classical horizontal structural variables such those measured in field inventories: stem density,

basal area and mean diameter. Although to date, fewer studies have investigated the relationship between canopy features and these variables, the underlying theory remains the same as for the AGB. For example, using texture indices provided by the Fourier transform textural ordination (FOTO) on high-resolution images, [Couteron et al. \(2005\)](#) were able to obtain a very good correlation with these stand parameters ( $R^2$  value up to 0.8 and 0.71 for tree density and diameter of the tree of mean basal area respectively). [Drake et al. \(2002\)](#) also found strong correlations between large foot-print LiDAR waveform metrics (i.e. Height of Median Energy of the waveform: HOME) and AGB, basal area and mean diameter ( $R^2$  values up to 0.93, 0.72 and 0.93 respectively). Finally, as for diversity assessments, recent studies on forest structure have seen increasing development of technologies using UAS which brings promising perspectives (e.g. [Ota et al. 2017](#)), especially for developing countries.

## **4. Discussion**

### 4.1 Field-based and/or remotely-sensed data?

For both methods, there are tradeoffs in terms of coverage, accuracy and cost effectiveness (Fig. 1), depending on the type of data needed to address the research objectives. Since remote-sensing methods only allow assessments of trees visible from the sky (i.e. canopy), a lot of information on both tree species diversity and forest structure is lost. In addition, technological constraints and environmental conditions, such as cloud cover, sun angle and topographic shadow, might also limit their use ([Song et al. 2015](#)). For that reason, the most accurate ways to collect biogeographical data on species diversity and forest structure still remain based on intensive field measurements. However, a strong limitation of field-based data is that their collection is very labour-intensive, and therefore very expensive to collect over large geographic areas ([Segura and Kanninen 2005](#); [Seidel et al. 2011](#); [Wang et al. 2011](#)). Assessments of tree species and forest structure on regional scales, such those used when studying forest fragmentation, are thus usually interpolated from relatively small field plots which can provide accurate estimates of species richness and forest structure at local scales. Nevertheless, because forest structure and tree species composition are spatially and temporally variable, interpolating data from a small number of plots to estimate species richness and forest structure for large areas is subject to high degree of uncertainty ([Clark and Clark 2000](#); [Palmer et al. 2002](#); [Saatchi et al. 2011](#)).



**Fig. 1** Spatial resolution and cost effectiveness of field-based and remotely-sensed methods for monitoring of tree species diversity and forests structure. UAS = unmanned aerial systems.

In contrast, remotely-sensed methods can overcome the limits of field-based methods by providing measurements of forests on larger geographic scales. While lacking the accuracy of most field-based observations, remote-sensing methods allow not only lower measurement costs and less time consumed, but also access to spatially-continuous data collection over large portions of the Earth's surface (Palmer et al. 2002; Asner and Martin 2009), including unreachable forests located in remote locations or areas where conditions are dangerous. Moreover, considering that many important natural and human-induced forest disturbances occur at fine spatial scales, such as tree falls and selective logging, remote-sensing has immense potential to improve our understanding of the magnitude of biomass changes at multiple scales (Houghton 2005). Thus, while field measurement methods will remain insufficient to regularly sample large or poorly-accessible areas, especially in the tropics, monitoring methods combining field and remotely-sensed data could provide cost-effective answers to forest monitoring challenges (Asner et al. 2010).

Based on this analysis, we also suggest these two approaches, ground-based and remote-sensing, should be complementary when applied to studies of fragmented forests. This conclusion also meets the recommendations from a review by [Bustamante et al. \(2016\)](#) that focused on the assessment of effects of tropical forest degradation on carbon stocks and biodiversity. Moreover, while unsupervised species classification using remote-sensing is able to predict the diversity of tree species, only ground-based inventories can provide accurate information about species composition. However, while we recognize the value of field-based inventories, a tradeoff must be made between the amount of information collected and its quality. When studying fragmented forests, it is important to assess as many forest remnants as possible in order to evaluate conservation values at the regional scale or even wider. A combination of remote-sensing and ground plots could thus provide regional scale monitoring of forest fragments and facilitate good choices in the management of those fragments. Despite their lower accuracy, remotely-sensed data could be used to map both tree species diversity and forest structure over landscape scales in order to identify priority areas for conservation. Once these priority areas have been identified, field-based measurements could be used within them to provide relatively accurate information on forest diversity and structure at a local scale and allow validation of remotely-sensed data.

To achieve this, small plots of 0.1-0.2 ha, such as the 20 × 50 m plots proposed by [Arellano et al. \(2016\)](#), seem well suited for a fragmented landscape with small and irregularly shaped forests, as they could fit in most of the forest remnants. Although the minimum diameter measurement of 2.5 cm used in this method would necessarily provide better results, we suggest that a minimum diameter of 10 cm seems more suited for time- and cost-effective assessments. Thus, for a 0.1-ha plot it would be only necessary to measure trees  $\geq 10$  cm DBH within 10 m of a central 50 m transect line, without the need for time-consuming surveys of plot corners or boundaries. Finally, we suggest adjusting the number of plots per forest remnant as a function of the remnant size: the bigger the remnant, the more plots will be necessary for accurate assessments. Doing so approximates the method suggested by [Baraloto et al. \(2012\)](#), except it uses larger 20 × 50 m transects and allows practical application to fragmented tropical forests even when remnants are relatively small. However, further research needs to be done to validate this approach. Optimal plot size, as well as the number of plots and area sampled, will depend on the forest being studied, study objectives, and resources available.

Considering the use of remote-sensing data, along with the 10 cm DBH cut-off in the field-based method, we concede that this approach only focuses on canopy trees and does not account for the understory diversity (i.e. tree species that are not likely to grow into larger size classes). However, given the role played by canopies in mediating interactions among biota ([Janzen 1970](#)) and providing an environment for other flora and fauna

(Connell 1978; Orians et al. 2012), canopy-tree diversity is usually seen as a good proxy of general biodiversity (Gentry 1988).

#### 4.2 Remotely-sensed techniques: a matter of tradeoff?

Having also decided to use remote-sensing approaches in assessing fragmented tropical forests, one fundamental question remains: which approach should be chosen? Again, all approaches have pros and cons and the most appropriate largely depends on (1) the quantity of resources available and (2) the type of data needed to address the research objectives. The remote-sensing methods reviewed earlier are compared in Table 4 for their specific applicability to fragmented forest studies. The final chosen technique might be different from one study to another since the decision has to be based on the tradeoff between "data quality vs cost effectiveness".

Table 4 : Summary of remote-sensing techniques that could be used for assessment both of species diversity and forest structure in fragmented tropical forests. The technique presenting a good tradeoff between data quality and cost-effectiveness is presented in bold. UAS = unmanned aerial systems.

Method	Spatial resolution	Spectral resolution	Cost effectiveness	Labor requirements over regional scale	Coverage	Accuracy
Landsat (TM, ETM+)	Medium	Medium	Free	Less labour	Very large	Low
Sentinel-2	Medium	Medium	Free	Less labour	Very large	Medium
IKONOS/GeoEye/Quickbird	High	Low	Medium cost	Less labour	Very large	Medium/High
<b>WorldView</b>	<b>High</b>	<b>Medium</b>	<b>Medium cost</b>	<b>Less labour</b>	<b>Very large</b>	<b>High</b>
Airborne spectrometer/LiDAR	Very high	Very high	Costly	Laborious	Limited	Very high
UAS	Very high	Very low	Economical	Very laborious	Limited	Very high

An important issue in remote-sensing studies of tree species diversity and forest structure is the scale, as results are dependent on the pixel resolution (Rocchini et al. 2015). As mentioned earlier, the 30 m resolution of multispectral data from Landsat-TM/ETM+ satellite imagery is regarded as not good enough for assessments of species diversity and forest structure at landscape scales. Even if Landsat imagery has a higher spectral resolution than QuickBird or IKONOS sensors, the addition of redundant data can increase noise without adding valuable information, by including spectral information not related to habitat heterogeneity as noise in statistical models (Bajwa et al. 2004). On the other hand, Roth et al. (2015) recently suggested that using coarse spatial resolution (> 20 m) could increase accuracy across ecosystems. However, this conclusion was based on temperate ecosystems and authors acknowledged that this result might not be true for more complex ecosystems such as tropical forests, especially when they are fragmented.

Roth et al. (2015) discussed the important role played by patch characteristics (i.e. both size and shape) in classification success. Although the term "patch" in this study was related to a patch of the same species (or class of species) within the habitat, this discussion might be transposed to forest patches in fragmented forest studies. Roth et al. (2015) hypothesized that highest accuracy would be achieved when pixel resolution most closely approximates a species patch size and that, at coarse resolution, species occurring only in small patches cannot be mapped. This is a problem in tropical forests where almost every tree crown within a single hectare might belong to a different species; thus species patches are very small, which requires high spatial resolution. Coarse resolution is also not able to represent the edges of irregularly shaped patches as clearly as high-resolution imagery (Karl and Maurer 2010; Roth et al. 2015), the proportion of edges being much higher than in equivalent round patches. This is a crucial limitation considering that most global forest fragments present irregular shapes. These limitations also apply to spaceborne LIDAR systems, such as GLAS, or the upcoming GEDI sensor (Stavros et al. 2017). Although aimed at making height, canopy and above ground biomass metrics freely accessible, their large footprint (70 m for GLAS and 25 m for GEDI) make them very likely unsuited for assessment of forest structure in fragmented tropical forests. Thus, higher resolution is necessary to avoid too many pixels encompassing mixed species patches or habitats.

Satellite imagery such as Landsat-TM/ETM+ and GEDI sensor might still be useful for studies at continental scales (e.g. Taubert et al. 2018) where medium resolution is not as important since the region of investigation is very large. Ultimately, for studies with very limited funding, although relatively coarser in terms of quality, data accessible for free might be the only possible option. In such conditions, we recommend the use of Sentinel-2 data over Landsat imagery, as it offers a slightly higher spatial and spectral resolution. Sentinel-2a (launched 2015) and Sentinel-2b (launched 2017) have a five-day repeat equatorial overpass and offer a 10 and 20 m spatial resolution for eleven multispectral bands (the 60 m resolution of two other bands being too low). This imagery should be able to provide rough estimates of tree diversity and forest structure in fragmented forests, although further research needs to be done to validate the use of this method.

Otherwise, high-resolution imagery is needed for more accurate studies at regional scales and could be achieved using either spaceborne or airborne sensors. A problem inherent with the use of satellite-based observations in the tropics, especially in mountain areas, is the common presence of persistent cloud cover that may severely limit their use (Ticehurst et al. 2004). A solution can be the use of airborne platforms since measurements can be planned around local cloud cover dynamics. In addition, airborne techniques offer far more spectral information

than current satellite-based approaches, which is very useful for species identification and characterization of forest structure. However, the coverage of these airborne techniques is usually limited by their small swaths and their very high cost per hectare covered, due to the use of either planes or helicopters. This review aims to make recommendations for rapid and cost-effective assessments in fragmented tropical forests. Since most of this topic concerns developing countries, it is likely that these types of airborne sensors may be prohibitively costly and inaccessible for researchers, except when funded by developed countries.

For fragmented tropical forests, we suggest as a good compromise the use of high-resolution imagery from satellite sensors such as IKONOS, Quickbird or Worldview. They offer the advantage of allowing reasonably accurate estimates of both canopy diversity and forest structure using a single sensor (i.e. no need for additional data such as LIDAR) while being immediately available for medium costs over very large areas. Moreover, considering the decrease in cost for such images observed over the last decades, it is to be expected that they will become even cheaper in the future, making them affordable even for researchers with limited funding. In contrast with airborne systems, a limitation to diversity estimation using such imagery might be the absence of hyperspectral data. However, while hyperspectral data are needed for species identification, we believe that the multispectral data provided by these sensors might be enough for an approximate prediction of species diversity. Worldview particularly is able to provide images with up to eight spectral bands at a resolution of 2 m, which is probably enough to provide relatively good estimates of both species diversity and stand structure.

Concerning the problem related to cloud cover using satellite imagery, the combination of several images should be able to produce a cloud-free image in most cases. Ultimately, for areas with consistent cloud cover all year long (as reported by [Asner \(2001\)](#) in some parts of Brazilian Amazonia), a cost-effective alternative might be the use of UAS. Drones can provide high-resolution imagery, as well as hyper spectral images and LiDAR data. In the literature, recent studies using UAS have been able to record high-resolution images of areas from less than 100 ha ([Ota et al. 2017](#)) up to about 2500 ha ([Michez et al. 2016](#)). Theoretically, although considerable time might be necessary for image acquisition and georeferencing, this approach can be used over much larger areas. However, this promising approach still needs to be developed and described in further studies, especially in more complex ecosystems such as tropical forests. Thus, for now, this recommendation only applies when the use of high-resolution imagery from satellite sensors is impossible.

## **5. Conclusion**

Assessment of both tree species diversity and forest structure is needed at local and regional levels to understand the present status of fragmented tropical forests and to develop effective management strategies for their conservation. In this paper, we have reviewed a range of candidate sampling techniques and measurement methods with potential to achieve these objectives. For most studies, the availability of time, money and manpower is the major constraint. Several methods using either ground-based or remotely-sensed techniques were discussed in this review in order to identify candidate methods for rapid and cost-effective assessments of tree species diversity and forest structure in fragmented forests. To summarize, the methods should satisfy the objectives of the study and also characterize the inherent diversity status of a region of investigation at acceptable costs. We suggest combining the use of both field-based and remotely-sensed methods to achieve that goal as these methods can be complementary. Remote-sensing data should be used to predict and map the tree species diversity and stand structure at regional scales, while field-inventories provide accurate information at local scales and allow validation of remotely-sensed data. For field-based inventories, we recommend the use of small (e.g. 20 × 50 m) plots with a 10 cm DBH minimum measurement. If funding is not a problem, airborne imagery seems the best in terms of quality of information (i.e. hyperspectral and hyperspatial imagery, LiDAR). A more cost-effective alternative providing reasonably accurate estimates would be the use of high-resolution satellite imagery such as Worldview. Ultimately, for studies where data accessible for free is the only possible option, we recommend the use of Sentinel-2, although it is relatively coarser in terms of quality. In any case, further research needs to be done to validate these approaches in fragmented tropical forests.

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