Factors influencing the estimation of aboveground biomass (AGB) in tropical forests using RADAR remote sensing.

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Abstract

Despite the large amount of accessible spatial information, the issue of estimating aboveground biomass through remote sensing, especially radar, remains a challenge in complex ecosystems such as tropical forests. One of the advantages of radar sensors is that of "crossing clouds" (capacity that does not have optical images like Landsat), facilitating their use in areas with permanent cloud cover. This work defines, from several studies conducted in tropical forests using ALOS PALSAR, which are the factors with the most influence on the signal of the radar. This can be useful in the development and/or improvement of methodologies to estimate aboveground biomass in tropical forests, combining field data and satellite imagery of radar.

Keywords: biomass, radar, ALOS PALSAR, remote sensing, L-band.

Introduction

In recent years, the estimation of aboveground biomass (AGB) through the combination of field data and remote sensing has been gaining ground, because it becomes an option that reduces costs, in addition to obtaining information in areas of difficult access (Koch 2013).

Biomass is the total amount of plant material present in a specific area (Drake et al., 2003). The aerial component of the arboreal stratum represents one of the main stores of biomass and carbon (Quijano & Morales 2016). There are several methods to estimate AGB, being classified as destructive or direct (cut, dry and weigh the tree) and non-destructive or indirect (allometric equations) (Sola et al., 2012, Walker 2011). Allometric equations usually include three variables: diameter at breast height (DBH), tree height and wood density; through which we can obtain the ABG in the field.

The estimation of AGB using remote sensing remains a challenge, especially in such complex ecosystems as tropical forests (Hamdan et al., 2014b). Research conducted by Avitabile et al. (2015), Baccini et al. (2012), Goetz et al. (2009) and Mitchard et al. (2013) using optical and / or radar images show different methods used for the estimation of AGB and carbon stocks by remote sensing in tropical forests around the world. They emphasize the ability of radar satellite images such as ALOS PALSAR to "pass through the clouds" (capacity with which optical images do not count as LANDSAT), this feature being very useful in tropical areas with permanent cloud cover.

Although there is little information available that indicates exactly what climatic or biophysical factors affect the estimation of AGB in tropical forests at local scales; Studies such as those by Hamdan et al. (2014b), Sinha et al. (2015) and Espinoza-Mendoza (2016) provide valuable

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information. Hamdan et al. (2014b) found in Malaysia, that the allometric equations have a great influence on the response of the sensor when estimating biomass. In addition, the size of the trees and the diametric groups also influenced the estimated biomass values by means of radar images. On the other hand, Espinoza-Mendoza (2016), found in the forest of Nicaragua, that the number of trees per hectare is a very important factor when correlating the backscattered value of the radar with the biomass estimated in the field.

The present work aims to define, based on various studies in tropical forests, which factors are those that would have a greater influence when estimating biomass by radar images (especially ALOS PALSAR). It should be noted that in this research, factors referring to technical and structural aspects of the forest are mentioned, focusing more on the latter. Knowing these factors and the level of influence that hold, would be of great support in the development and / or improvement of methodologies for estimating ABG in tropical forests combining field data and remote sensing.

Technical aspects of radar images: wavelength and polarization

The frequency of the SAR radar is directly proportional to the depth of penetration of the wave, meaning that short waves can only penetrate the forest by a few centimeters while long waves can interact with the forest floor (Imhoff 1995). The L band is the least influenced by the environmental conditions, therefore, it obtains better information of the structural components of the forest by having a better interaction with the trunk and the branches, being the most adequate for estimating biomass (Ghasemi et al. 2011, Joshi et al 2015b, Luckman et al 1997, Yu and Saatchi 2016).

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In the same way, the P band has a good correspondence with the biomass. Both long wavelengths can penetrate the canopy, dispersing the energy towards the woody components, being related to biophysical parameters of the trees (Sinha et al 2015, Yu and Saatchi 2016). On the other hand, the X band, is dispersed by the leaves and surface of the canopy, which is feasible to obtain access to the information of the upper layers of the trees. While the C band penetrates through the leaves being dispersed by small branches and elements of the intermediate canopy (Ghasemi et al., 2011). The signal of this last length, although it is true to some extent extends beyond the canopy, becomes attenuated when into contact with more closed canopies and with more structural components, so it works best only in coverage with low amount of biomass (Ghasemi et al., 2011), being less sensitive to the increase in forest volume than the L band (Puliainen et al., 1999).

On the other hand, the polarization of the signal is related to the direction of the electric field of the electromagnetic waves and depends on the interaction between the signals emitted and the reflective elements (Sinha et al., 2015). The radar signals are emitted in four polarization combinations: horizontal (HH), vertical (VV) or crossed (HV, VH) (Ghasemi et al., 2011). All these types of polarization will be influenced by the vertical and / or horizontal structure of the forests; so they will interact with different orientations and structures of their components.

Several studies have shown the superiority of HV polarization over HH polarization, indicating that HV has a greater sensitivity with biomass, being less influenced by soil moisture and vegetation (Behera et al., 2016, Collins et al., 2009). Hamdan et al 2011, Michelakis et al 2015, Sandberg et al 2011, Van Zyl 1993). On the contrary, studies such as those of Wang et al. (1995) indicate that HH polarization can provide a good means of estimating biomass in coniferous forest. This polarization interacts in a better way with the trunk and biomass of the canopy (Beaudoin et al., 1994), presenting a direct surface-trunk relationship (Wang et al., 1995).

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Finally, we consider that bands of long lengths such as L or P, with cross polarizations such as HV or VH, give better results than short wave bands such as C or X with simple polarizations HH or VV (Dobson et al., 1992; Le Toan et al. 1992).

Alometry

Allometry is one of the factors related to the most important forest parameters to be considered, probably well above the elaboration of the biomass model. The use of allometric equations that consider three basic parameters: diameter at breast height (DBH), tree height and wood density of the species, can give us more accurate estimates.

In some cases, the presence of biases is unavoidable due to inaccuracies on measurement parameters on the field, we must consider evaluating the use of each of them (Keller et al., 2001, Ketterings et al., 2001). Whereby, it is key to consider the methodology used for its calculation. If we do not know the methodology, we doubt about this or observe data inconsistencies, such as the lack of use of specialized instruments to measure heights; we recommended use equations that only consider DBH, since our results could be over or underestimating the AGB and therefore the model results.

We will consider that the use of local allometric equations for a particular type of forest or species can give us a more accurate estimate. But if this were not the case, generic equations like Chave et al. (2014b), Brown (1997) updated by Pearson et al. (2005), Feldpausch et al. (2006), among others, provide excellent estimates considering the indicated parameters (Table 1).

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For example, Hamdan et al. (2014a) used five allometric equations, determining that the best correlation with the radar signal was the allometric equation of Kato et al. (1978). While Espinoza-Mendoza (2016) worked with Brown's equations (1997) updated by Pearson et al. (2005) developed for tropical forests and Chave et al. (2001); both equations only consider the DBH parameter. In the case of Espinoza-Mendoza (2016) no significant statistical differences were found between both equations, so it was decided to use the Brown equation (1997) updated by Pearson et al. (2005).

Aspects of the forest structure: density, heterogeneity, diameter groups and types of dispersion in forests.

There are studies using remote radar sensors that have estimated biomass in tropical forests. Most of these have been carried out in coniferous forests and pine savannas, justifying that the sensor cannot be used in dense tropical forests or in forests with biomass greater than 100 Mg ha-1 (Mermoz et al., 2014b; Mitchard et al., 2009; Woodhouse et al., 2012). Therefore, it is considered that the density and structural complexity of some forest types can have a great influence on the L band of ALOS PALSAR (Michelakis et al., 2015). The work carried out by Espinoza-Mendoza (2016), pioneer in Nicaragua, and one of the first in Central America to discuss the role of the factors that impact on the estimation of biomass with radar in broadleaf and coniferous forests, found a big difference in correlating both types of forest with the radar signal. The study showed that the coniferous forest correlated quite well ($n = 40$, $r\rho = 0.64$, pvalue <0.0001), while the broadleaf forest obtained a low correlation, which only improved when considering> 80ind per plot of 0.5ha (160 ind / ha) ($n = 34$, $r\rho = 0.60$, pvalue <0.0002).

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Observing these results, we consider that the structure of both forests would be one of the causes. This can be supported by Michelakis et al. (2015) who mention that, sometimes, the weak relationships between the backscatter coefficient and biomass are due to the structural variation of the canopy and the number of trees present in the plots. Therefore, we will discuss the behavior of the radar signal separately for coniferous forests and broadleaf forests.

A coniferous forest is structurally less complex than a broadleaved forest (Figure 2). The areas where these forests are located are more open, with low canopy cover and the presence of clearings and/or gaps in the terrain. Therefore, at lower complexity, the radar signal should be dispersed more homogeneously without the influence of a variety of dispersing elements.

We can consider that, in a coniferous forest, the type of dominant dispersion would be double bounce (Figure 4), because, when there is exposed soil, the signal is emitted towards the ground, bounces off the trunk and then disperses towards the radar, improving the sensitivity of this (Hensley et al., 2014). In addition, in some areas, coniferous forests are not very dense, so the L band would have a positive contribution (Yu and Saatchi 2016).

Wang et al. (1995) indicate that the largest amount of biomass of a conifer tree is stored in its trunk. So, it can indeed that to exists double bounce dispersion with surface-trunk interaction, the radar signal would be collecting direct information of the component with higher biomass (trunk). On the other hand, the volumetric dispersion (Figure 4) in this type of forest is very small, which would not contribute significantly in the results of the correlation.

The homogeneity present in coniferous forests is not a main feature of a tropical broadleaved forest, since in this last case exists a diversity of species, considered as heterogeneous forests (Figure 3). The high variability in its components: trunks, branches, leaf shapes, heights,

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densities, fruits and/or seeds, various moisture contents, among others, will have a positive or negative influence on the radar response.

The type of dispersion present in broadleaved forests varies (Figure 4). The volumetric dispersion encourages direct backscattering of both the soil, trunk and crown (De Miguel and Gutiérrez 2000, Watanabe et al., 2006). If our broad-leaved forest were homogeneous, it is very likely that there are no marked differences between correlations with sparse and dense forests, as was the Espinoza-Mendoza study (2016), but this is not the case. Therefore, it is necessary to consider a distinction in radar response in sparse broadleaf forests and dense broadleaved forests.

The double bounce type dispersion could occur in a sparse or very sparse broadleaved forest, due to the existence of voids in the ground with exposed soil. If we consider some of these forests thin as forests in early successional stages, according to Mermoz et al. (2014b) biomass would be overestimated.

In dense broadleaved forests, volumetric dispersion will predominate, which will obtain information of all the components present in the middle and lower layers of the canopy, the signal would be attenuated when reaching the ground due to the density of this forest (Joshi et al., 2015a). Linked to this, very dense broadleaved forests are usually mature forests, where the radar signal has a better correspondence than in younger forests (Mermoz et al., 2014a).

The diametric groups also fulfill an important factor to achieve a good correlation between the biomass estimated in the field and the backscatter coefficient. For example, the study by Hamdan et al. (2014b) showed that the DAP > 30 cm obtained a better correspondence with the radar signal in Malaysian forests. These forests are dominated by dipterocárpeos of low lands, present in areas dedicated to the production of wood with logging activities since the '70s. Espinoza-Mendoza (2016) found that when considering the biomass of individuals> 10cm, the best correlation was obtained for broadleaf and coniferous forests throughout seven municipalities in

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the central and northeastern region of Nicaragua, in areas where hypothetically a forest transition would be occurring (Table 2).

Through figure 5 we could explain some factors such as the diametric groups: (a) it would represent a very dense broad-leaved forest (without gaps in the ground) that considers tree biomass with DBH> 10cm, with great variability in heights and components. The radar signal in this type of forest would be dispersed volumetrically attenuating as the canopy penetrates towards layers closer to the ground, (b) represents a dense broadleaved forest including biomass of individuals with DBH> 30cm, as in (a) the heights and components have some degree of variability. maintaining a good correlation, (c) represents a broadleaved forest considering only the biomass of individuals with DBH> 50cm, in which not only a volumetric dispersion can be generated, but also a double bounce dispersion. It is observed in table 2 that the correlation decreases significantly. Finally (d) represents a broadleaf forest where only the biomass of trees with DBH> 70cm is considered, probably high-altitude trees, indicating that there is no correlation with the radar signal (Table 2), and that the signal interacts strongly with the components of middle and lower layers, demonstrating for this case that it is not the larger trees that influence the radar signal.

Saturation level

One of the biggest problems with radar images is the saturation of the signal. Ghasemi et al. (2011) consider that the radar signal in complex tropical forests in L and P bands saturates around 100 Mg ha-1. Contradictory, Le Toan et al. (2011); Saatchi et al. (2011) and Sandberg et al. (2011) consider that the P band would be saturating from 300 Mg ha-1. In areas considered simple structure and where there are between 1 and 2 species, saturation may occur around 250

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Mg ha-1. On the other hand, Watanabe et al. (2006) indicate that the saturation level for a single conifer species using the HH polarization was 200 Mg ha-1, whereas if a variety of species (heterogeneous forest) is included, the saturation can vary depending on the polarization: VV = 50 tn / ha, HH = 100 tn / ha and HV => 100 tn / ha. As noted, there are different levels of saturation, which will depend to a large extent on the type of polarization used, wavelengths, types and structures of forests and number of species (Figure 6).

Masking forest and no forest areas

This factor, although it is true, does not directly influence to the developing model, but, it can have a strong impact when is considered as an external resource. Many areas considered forest may not be so in reality, due to land cover and land use maps are elaborated with different methodologies. Morton et al. (2014) consider that these external resources would cause an impact on the estimated biomass values. Therefore to mitigate to some extent this kind of source of error, we can use a visual review of the plots from which the data were obtained. Supported by tools such as Google Earth, field technical files used at the time of the information gathering of the plots, forest maps and/or high resolution multispectral images that correspond to the dates close to the data collection.

Conclusions

1. To estimate biomass in tropical forests using remote radar sensors, the structural characteristics of these should be considered. Because the radar signal, especially the L and P bands act directly with the vegetation components present in these forests.

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2. Specific equations should be developed for each type of forest. If in a landscape we have: broadleaf forest, coniferous forest, riverside forest and mangrove forest, the best method to obtain good results will be the development of specific models for each type of forest, considering its structural components.

3. Generic methodologies, can cause considerable variations in the ABG, by not considering forest parameters related to local areas.

4. Generate more information related to the factors that affect the estimation of biomass in tropical forests using remote radar sensors is key to know how the structure of tropical forests, which is highly complex, affects the different bands, polarizations and scattered signals for the components of the forest.

5. Analyzing and comparing the multitemporal behavior of the radar signal between tropical forests and agroforestry systems in the tropics, is key to generating information related to forest transitions processes.

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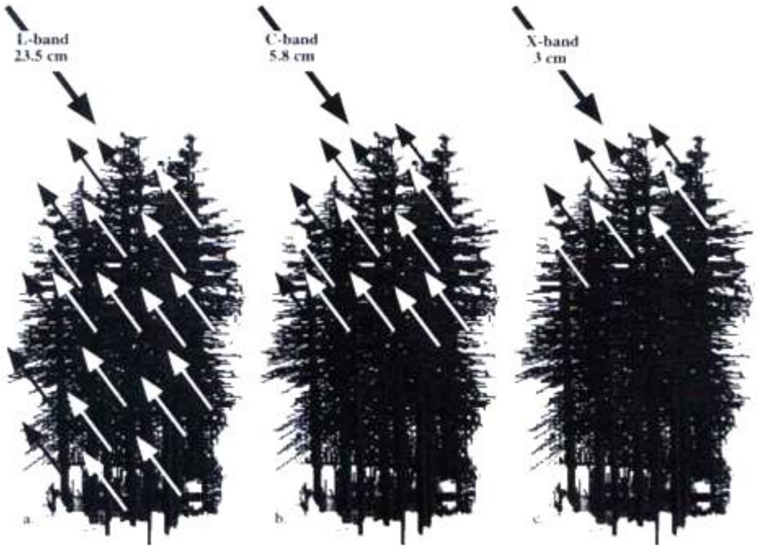

Figure 1: Wavelengths. The arrows indicate the penetration capacity of the X, C and L bands through the canopy (Jensen 2000).

Table 1: Diversity of allometric equations to be considered for the estimation of biomass using data taken in the field (Own elaboration).

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Referencia	Modelo alométrico
Chave et al. (2005)	$\rho X exp(\alpha + \beta_1 (\ln(DAP)) + \beta_2 (\ln(DAP))^2 - \beta_3 (\ln(DAP))^3)$
Chave et al. (2014a)	$\ln(AGB) = \alpha + \beta \ln(\rho * D^2 * H) + \varepsilon$
Brown (1997) Seco pp=900-1500mm	$B = 0.2035 * DAP^{2.3196}$
Brown (1997) Húmedo pp=1500–4000mm	$B = \exp(-2.289 + 2.649 * \ln(DAP) - 0.021 * \ln(DAP^2))$
Brown (1997) Muy Húmedo (pp > 4000mm)	$B = 21.297 - 6.953 * DAP + 0.740 * DAP^2$
Chambers et al.(2001)	$\mathrm{B} = \exp(\alpha + \beta_1 \ln(DAP) + \beta_2 (\ln(DAP))^2 - \beta_3 (\ln(DAP))^3)$
Burger (2005)	$\mathrm{B} = \exp(\alpha + \beta_1 \ln(Dbase))$
Tiepolo et al. (2002)	$B = \alpha + \beta_1 (DAP) + \beta_2 (DAP)^2$
Feldspausch (2012)	$B = \exp(a + b \ln(DAP) + c(\ln(DAP))^2 - d(\ln(DAP))^3 + e \ln(\rho w))$

(a) (b)

Figure 2: Sketch of mature coniferous forests. A dense and homogeneous (a) profile is observed, representing a coniferous forest in which a specie predominates. While (b) shows a forest of conifers with multiple strata, with different stages of growth, less dense than (a), with greater variability in heights and where 2 or 3 species of pine would predominate. Even so, it is observed that their structures have a greater homogeneity than a broadleaved forest.

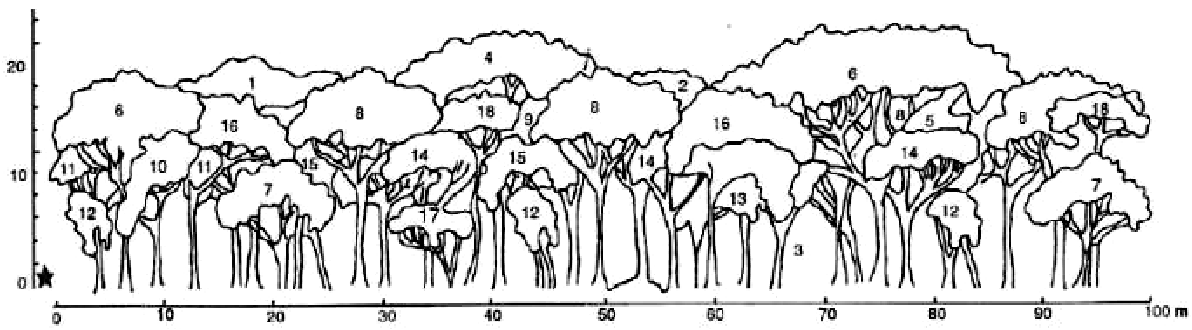

Figure 3: Louman (2001). The scheme shows the idealized profile of a wet forest premontane transition to tropical (Holdridge and Grenke 1971). There is a variety of heights, trunk forms, canopy, branches and each number represent a different species.

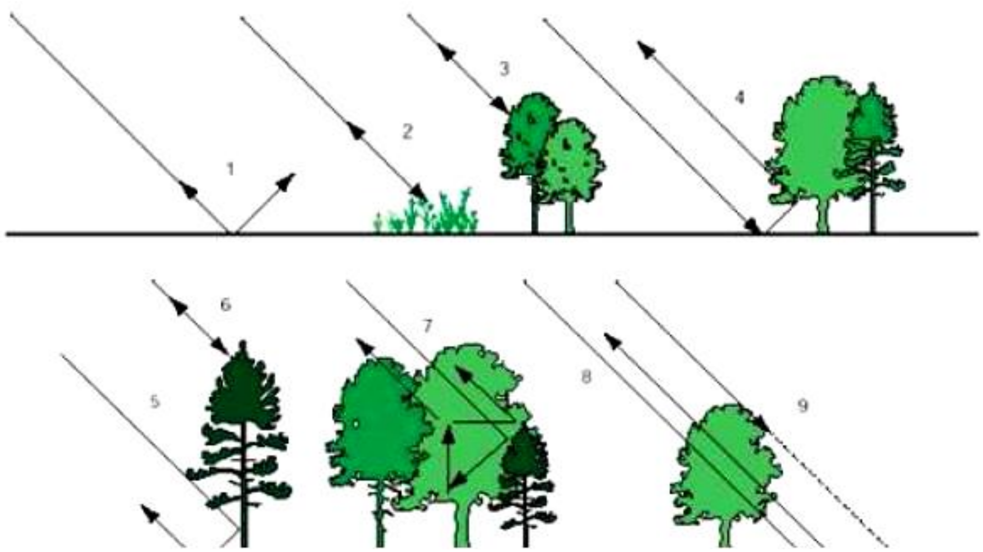

Figure 4: Different types of dispersion present in a forest (Piwowar, 1997) (1) Diffuse dispersion from the surface (2) and (3) Direct dispersion of various components of the vegetation (4) Double dispersion rebound of the soil interaction - vegetation (5) Corner reflection between trunk and surface (6) Direct backscattering of the upper layer of the canopy (7) Volumetric dispersion from

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within the canopy (8) Diffuse dispersion from the surface (9) Shadows caused by parts of the forest canopy or other parts of the canopy and / or the surface.

Table 2: Correlations between the biomass present in different diametric groups and the radar signal (Espinoza-Mendoza 2016).

DAP	Pearson	# de parcelas
≥10cm	0.74(p<0.0001)	74
≥20cm	0.73(p<0.0001)	72
≥30cm	0.67(p<0.0001)	65
≥40cm	0.57(p<0.0001)	53
≥50cm	0.50(p<0.0001)	46
≥60cm	0.34(p<0.1100)	34
≥70cm	0.13(p<0.5351)	26

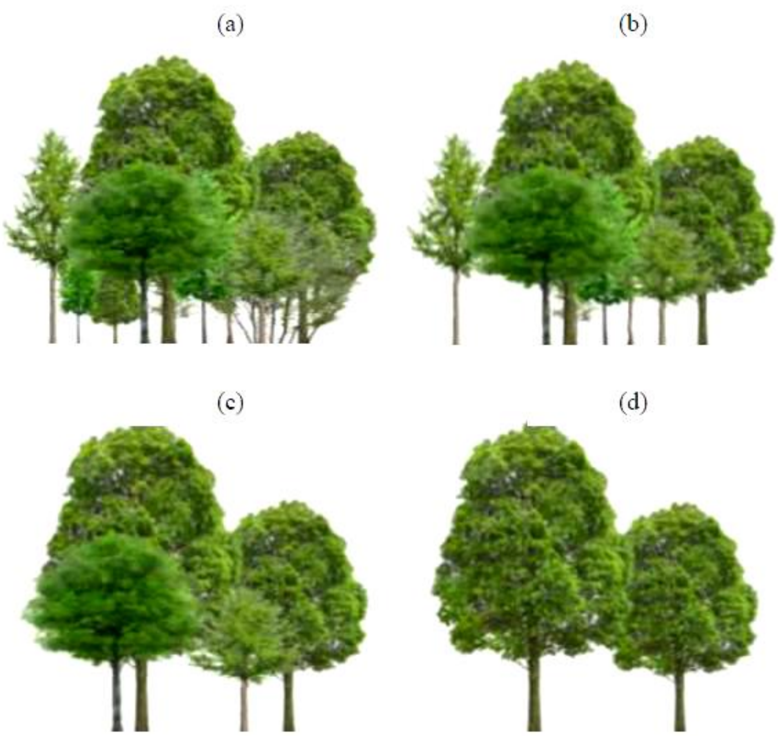
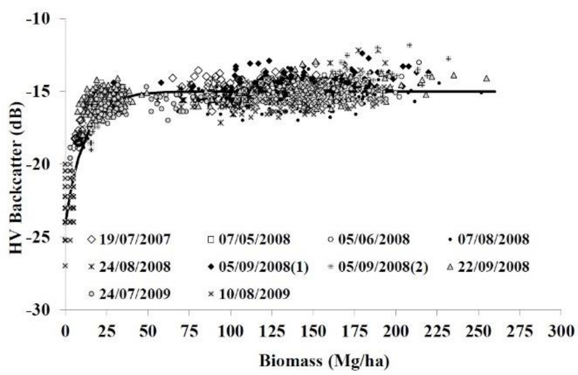
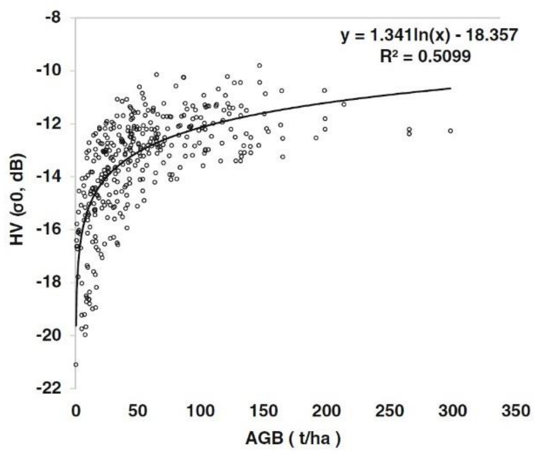


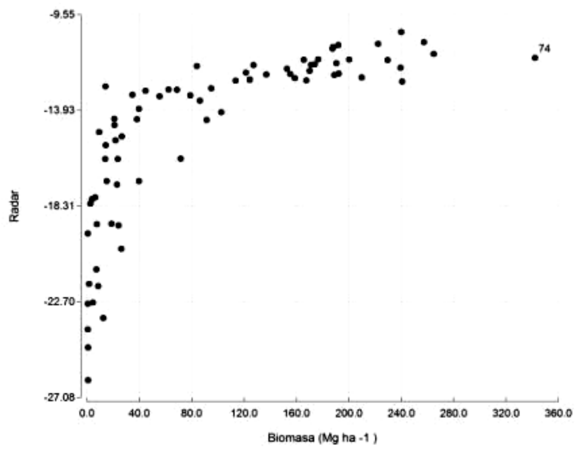
Figure 5: Forest structure and biomass (Espinoza-Mendoza 2016).


HV Backcatter (dB)
Biomass (Mg/ha)
19/07/2007
07/05/2008
05/06/2008
07/08/2008
24/08/2008
05/09/2008(1)
05/09/2008(2)
22/09/2008
24/07/2009
10/08/2009

(a)


y = 1.341ln(x) - 18.357
R² = 0.5099
HV (σ0, dB)
AGB (t/ha)

(b)



(c)

Figure 6: Different levels of saturation. Biomass estimated in field vs HV. a: Baghdadi et al. (2015) around 60 Mg ha-1 in eucalyptus plantations in Brazil in HV polarization; b: Thumaty et al. (2016), greater than 150 Mg ha-1 in HV polarization in deciduous forests in India; c: Espinoza-Mendoza (2016), around 130 Mg ha-1 in Nicaraguan forests.