Jomar Magalhães Barbosa

**Estimativa de estrutura biofísica florestal de Mata Atlântica em
áreas declivosas por meio de sensores remotos**

**Remote sensing of forest biophysical structure of Atlantic
Rainforest over steep slopes**

Maio – 2013

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Dedicatória

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CAPÍTULO 1

INTRODUÇÃO

CAPÍTULO 1

INTRODUÇÃO GERAL

1 – O Sensoriamento remoto na estimativa de variáveis biofísicas da vegetação

A transformação de informações espectrais ou de pulsos de energia de sensores remotos em variáveis ecológicas complementa o uso tradicional das imagens de satélite para elaborar mapas de classes de uso do solo (Boyd e Foody, 2011; Cabello *et al.*, 2012). As variáveis ecológicas obtidas pelos sensores remotos incluem cobertura foliar, absorção de radiação fotossinteticamente ativa (Glenn *et al.*, 2008), estoques de carbono e biomassa (Lu 2006), estrutura florestal (Lefsky *et al.*, 1999), dentre outras. A obtenção destas informações por meio de sensores remotos nos permite responder perguntas em um nível de escala regional ou global e complementa amostragens de campo (Mascaro *et al.*, 2011). No entanto, ainda existem diversos desafios técnicos e tecnológicos em relacionar, de forma acurada, variáveis ecológicas com dados dos sensores remotos (Lu, 2006; Eisfelder *et al.*, 2012).

As influências das ações humanas sobre as florestas tropicais são expressivas em um nível de escala regional e global (Vitousek, 1994). No entanto, nossa capacidade de entender processos ecológicos na escala de paisagem ainda é bastante limitada (Dahlin *et al.*, 2012). A identificação e mapeamento dos padrões e processos ecológicos na escala de paisagem dependem do nosso conhecimento em utilizar dados provenientes de sensores remotos. Apesar disso, muitos ecólogos ainda são conservadores em adotar novas técnicas ligadas ao sensoriamento remoto, como é o caso do uso de variáveis biofísicas da vegetação, derivadas do sensoriamento remoto, como insumo de modelos de mudanças ambientais (Newton *et al.* 2009).

Como em outros campos do conhecimento, novas ferramentas analíticas ajudam a obter melhores diagnósticos para identificar questões anteriormente não evidentes (Cabello *et al.*, 2012; Anderson, 2012). Por isso, deve ser dada uma maior atenção ao uso de inovações tecnologias do sensoriamento remoto na resposta de novas e antigas questões ecológicas. As análises ecológicas utilizando dados de sensores remotos devem ser acompanhadas de informações sobre acurácia e validação dos modelos. Estas informações são essenciais para aumentar seu valor de extrapolação espacial e temporal (Boyd e Foody, 2011).

As principais características da vegetação que interferem no sinal de um satélite do óptico são fatores químicos (pigmentos fotossintetizantes e água) e estruturais (organização dos tecidos foliares, disposição dos troncos e camadas e orientação foliar). A energia incidente sobre a vegetação pode ser absorvida, transmitida ou refletida conforme o comprimento de onda e características do alvo. A interação entre estes fenômenos determina o padrão do resposta espectral da vegetação analisada (Ponzoni e Shimabukuro, 2007; Jensen, 2007). Diferentes tipos de sensores remotos são utilizados para captar a energia refletida pelo dossel. Estes sensores podem ser ativos (energia emitida pelo sistema sensor) ou passivos (sensor capta energia solar refletida ou emitida pela Terra) (Jensen, 2007).

Existem desafios técnicos no processamento de dados de sensores remotos provenientes de áreas declivosas. A declividade pode gerar problemas de sombreamento (figura 1), diferenças anisotrópicas, iluminação difusa ou brilho causado pelo vizinho. No entanto, muitas perguntas ecológicas estão relacionadas a áreas com vegetação em declives ou mesmo ao efeito do relevo sobre variáveis ecológicas. Este é o caso da Mata Atlântica que, diferentemente da Amazônia, possui sua maior distribuição geográfica sobre áreas com grande complexidade topográfica.

Figura 1. Efeito da topografia sobre a diferença de incidência de energia (solar, radar ou laser) (adaptado de Riaño *et al.*, 2003). A seta indica a direção da energia (ativa ou passiva) que irradia na superfície. A área cinza representa a diferença de energia incidente em duas faces de um morro hipotético.

2 – Estrutura florestal em Mata Atlântica

A Mata Atlântica é uma das áreas com maior diversidade biológica no mundo (Dirzo e Raven, 2003). No entanto, este bioma sofreu redução da vegetação nativa por meio da ação humana em diferentes ciclos econômicos (Born, 2000; Dean, 1996). Foram desmatados aproximadamente 86,7% dos 1.315.460 km² originais (SOS Mata Atlântica/INPE, 2012). O que resultou em um grande número de fragmentos florestais pequenos, com baixa conectividade e a metade da área remanescente composta por mata secundária (Ribeiro *et al.*, 2009).

O desmatamento é apenas uma das consequências do grande impacto humano na Mata Atlântica. A caça, o fogo, o corte seletivo da vegetação e outros impactos antropogênicos também apresentam efeitos sinérgicos sobre a degradação e extinção de espécies em Mata Atlântica. Todo este contexto tem gerado uma taxa de extinção de 85% das populações de mamíferos em fragmentos florestais maiores que 0,1 ha (Canale *et al.*, 2012). Existe consenso sobre a elevada prioridade para se gerar ações de conservação na Mata Atlântica devido a sua

intensa perda de habitat, grande número de espécies endêmicas e alto número de espécies endêmicas por área (Myers *et al.*, 2000) que coloca o bioma de Mata Atlântica entre os “hotspots” do mundo.

Apesar deste cenário pessimista, dados empíricos têm demonstrado que algumas paisagens de Mata Atlântica estão experimentando um aumento de área (Baptista & Rudel, 2006; Baptista, 2008; Lira *et al.*, 2012). Existem recentes especulações de que este processo de regeneração poderia estar interligado com mudanças na cobertura da Floresta Amazônica (Pfaff and Walker, 2010; Walker, 2012). Isso porque o crescente aumento de áreas produtivas na Amazônia estaria reduzindo a expansão de área agrícola na Mata Atlântica, levando à diminuição do desmatamento e aumentando a regeneração da Mata Atlântica em alguns locais. Este processo estaria vinculado a recentes dispositivos legais que impedem o desmatamento na Mata Atlântica. A amplitude de regeneração da Mata Atlântica ainda não é conclusiva e requer maiores estudos.

As mudanças temporais na cobertura do solo da Mata Atlântica têm ocorrido de forma independente da área de cada classe de uso do solo e de forma não constante ao longo dos anos (Freitas *et al.*, 2010; Lira *et al.*, 2012). Esta dinâmica irregular de uso do solo resulta em uma estrutura da paisagem heterogênea, em diferentes níveis de escala. Apesar da inconstância nas tendências de mudança de uso do solo, a localização de estradas, a distância de áreas urbanas e a topografia têm sido fatores relevantes para explicar a permanência de áreas florestadas (Freitas *et al.*, 2010). Além disso, existe uma convergência entre persistência de fragmentos de Mata Atlântica brasileira e áreas declivosas (Silva *et al.*, 2008; Teixeira *et al.*, 2009), bem como em outras partes do mundo (Munroe *et al.*, 2007).

O aumento da diversidade biológica está associado ao avanço da sucessão florestal (Bowen *et al.*, 2007; Chazdon *et al.*, 2009). Isto porque as mudanças estruturais gradativas entre os estágios de regeneração das florestas secundárias também modificam a

disponibilidade de microhabitat e condições microclimáticas no interior da floresta (Pinotti *et al.*, 2012). Isso quer dizer que variáveis biofísicas da estrutura florestal podem auxiliar no estudo da relação entre heterogeneidade da paisagem e biodiversidade.

Um único fragmento florestal pode apresentar mais de um estágio de regeneração devido a ação humana passada (queimadas, ciclos agrícolas e corte seletivo) ou a condições ambientais particulares (solo, incidência solar e clima) (figura 2). Além disso, o processo de sucessão florestal também é determinado por aspectos intrínsecos da vegetação (riqueza e abundância de espécies) ou por fatores estocásticos. Portanto, a disponibilidade de hábitat em fragmentos florestais pode ser analisada em gradientes de adequabilidade de hábitat, dependendo do estágio de regeneração (Bowen *et al.*, 2007). Esta forma de análise é importante porque as espécies estão distribuídas de maneira contínua, dependendo de gradientes ambientais diretamente ligados a disponibilidade de comida, abrigo, espaço e clima (Fischer & Lindenmayer, 2006). Sendo assim, modelos que usam variáveis ambientais contínuas (biomassa florestal, por exemplo) para analisar conservação biológica fornecerão mais realismo aos resultados (Fischer & Lindenmayer, 2006; Pinotti *et al.*, 2012).

Figura 2: Interação entre os temas relacionados à heterogeneidade estrutural de fragmentos florestais. Setas contínuas indicam fatores que influenciam a estrutura florestal e setas pontilhadas variáveis biológicas descritas nos capítulos da tese.

O avanço da sucessão florestal está intimamente associado a incrementos na quantidade de biomassa e carbono estocados (Brown e Lugo, 1982; Brown e Lugo, 1990). Por outro lado, com uma alta taxa de fragmentação, os pequenos remanescentes florestais se tornam mais similares a florestas secundárias de estágios iniciais, indicando retrocesso no processo de sucessão devido intensidade de distúrbio por meio de efeito de borda (Groeneveld *et al.*, 2009; Santos *et al.*, 2008; Tabarelli *et al.*, 2008). Como consequência, ocorrem perdas no estoque de biomassa (Putz *et al.*, 2011).

Em torno de 50% da biomassa florestal é composta por carbono (Brown e Lugo, 1982). Por isso, existe uma crescente atenção aos ganhos e perdas da biomassa florestal mundial, visto que 60% do aquecimento global é atribuído ao aumento da concentração de dióxido de carbono na atmosfera (Grace, 2004). A manutenção dos estoques de carbono na vegetação tem sido visto como um importante serviço ecossistêmico (Grabowski e Chazdon, 2012). Uma importante questão é como medir estes estoques e como prevenir sua liberação na atmosfera (Grace, 2004). Existe um grande número de levantamentos sobre os estoques de biomassa na Amazônia (Anderson, 2012; Asner *et al.*, 2010; Li *et al.*, 2010;), no entanto, ocorre o inverso para Mata Atlântica.

3 – Gradientes ambientais

Além do efeito da ação humana na estrutura da vegetação, existem diferentes condições ambientais que também determinam a quantidade de biomassa e a velocidade da regeneração florestal. Estas condições são determinadas por proximidade de fontes de propágulo, nutrientes do solo, drenagem, latitude, incidência de iluminação solar, dentre outros. Cada gradiente atua sobre a vegetação de forma direta ou indireta (Austin e Smith, 1989).

Gradientes de tipo de solo e declividade explicam em torno de um terço da variação da biomassa acima do solo na Amazônia Central (de Castilho *et al.*, 2006). Na Floresta Atlântica, Alves *et al.* (2010) demonstraram uma clara relação entre variação topográfica e estrutura florestal. Em outro caso, diferenças na taxa de mortalidade de árvores em face norte ou sul de uma área declivosa estão relacionadas à direção de vento (Bellingham e Tanner, 2000). Em todos estes casos, as características geomorfológicas são importantes fontes de heterogeneidade ambiental e podem determinar a quantidade de biomassa em diferentes escalas de análise (Mascaro *et al.*, 2011). No entanto ele é um agente secundário (indireto) porque atua diretamente em outros fatores como tipo de solo, disponibilidade de água (de Castilho *et al.*, 2006) e incidência luminosa (Olseth e Skartveit, 1997; Bennie *et al.*, 2008).

4 – Objetivos Gerais

A tese foi estruturada em cinco capítulos, os quais abordam diferentes questões sobre modelagem de estrutura florestal que auxiliam a alcançar dois objetivos principais. O primeiro é o de estimar a biomassa e fechamento do dossel de Mata Atlântica localizadas em áreas declivosas por meio de sensoriamento remoto. O segundo objetivo, avaliar como estas informações podem ser utilizadas no estudo de sucessão florestal e do efeito do relevo na vegetação.

O capítulo introdutório evidencia a problemática o qual a tese se insere. Três capítulos principais (II ao IV) utilizam informações previamente publicadas juntamente com dados de campo, para avaliar o uso de imagens de satélite na estimativa de fechamento de dossel e biomassa de Mata Atlântica em áreas declivosas. Por último, a tese é composta por um capítulo de conclusão geral que agrega os principais resultados encontrados nos diferentes capítulos. De forma mais detalhada os três principais capítulos abordam as seguintes questões:

- O capítulo II avalia o uso do sensoriamento remoto no estudo de sucessão florestal por meio da estimativa de biomassa em regiões tropicais. O texto sumariza as principais metodologias já publicadas. Além disso, expõe as questões ecológicas discutidas na literatura, a partir dos estudos que estimam biomassa florestal por sensoriamento remoto.
- O capítulo III modela a biomassa florestal de Mata Atlântica em diferentes estágios sucessionais de regeneração. Outro ponto importante do capítulo é a avaliação do efeito da geomorfologia na estimativa da biomassa florestal com o uso de imagens de satélite ópticas.
- Capítulo IV discute o efeito do relevo acidentado na disponibilidade de radiação solar anual para a vegetação. Subsequentemente, avalia a relação entre diferenças de iluminação solar e o fechamento de dossel. Por fim, estima o fechamento de dossel utilizando diferentes sensores remotos (ALOS AVNIR-2 e Landsat).

5 - Contribuição de autores

Em todo o processo de elaboração da tese recebi o auxílio de diferentes colegas de trabalho por meio de discussões, sugestões e coautorias. Abaixo, estão listados os capítulos que compõem a tese e seus respectivos coautores.

Capítulo II: Aboveground biomass estimation by remote sensing: a review of the implications for forest succession studies in tropical forests.

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Capítulo III: Remotely sensed biomass over steep slopes: an evaluation among successional stands of Atlantic Rainforest, Brazil.

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Capítulo IV: Combining annual sunlight pattern and remote sensed data to evaluate forest canopy structure.

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CAPÍTULO 2

Aboveground biomass estimation by remote sensing: a review of the implications for forest succession studies in tropical forests.

CAPÍTULO 2

Aboveground biomass estimation by remote sensing: a review of the implications for forest succession studies in tropical forests.

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Abstract:

Understanding the succession patterns of tropical forests is an important issue for disentangling the processes behind landscape dynamics. Forest succession is followed by continuous structural changes over time and result in increases in aboveground biomass (AGB). New remote sensing methods (including different data sources, image processing and statistical methods) and uncertainty evaluations are constantly being developed to estimate biophysical forest changes. The objectives of this paper are to review the use of remotely sensed AGB estimations in tropical forest succession studies and to summarize the most frequent ecological inferences discussed in the literature and the methods used. Remotely sensed AGB are broadly used in forest management studies, conservation status evaluations, carbon source and sink investigations and studies of the relationships between environmental conditions and forest structures. We emphasize that uncertainties in AGB estimations are very heterogeneous and that the biases are related to sensor type, processing methodology, ground truth availability, and forest characteristics. The studies reviewed here indicate that the use of remotely sensed AGB inference is more reliable for the study of spatial patterns of forest succession and over large time scales. A correct selection of the methodological strategy should consider the availability of both ground truth data and technical limitations specific to the remote sensing approach to minimize uncertainties and create acceptable AGB estimations. Remote sensing of temporal patterns in biomass requires further study, in particular as it is critical for understanding forest regrowth at scales useful for regional or global analyses.

Keywords: Forest regrowth; aboveground biomass; tropical forest; remote sensing

1 - Introduction

Secondary and disturbed forests comprise roughly 30-50% of the area covered by tropical forests (Achard *et al.*, 2002; Grainger, 2008; Asner *et al.*, 2009b; Blaser *et al.*, 2011). These forests play important roles as habitats for animal and plant species (Wright, 2005; Chazdon *et al.*, 2009; Dent and Wright, 2009) and store significant amount of carbon per unit area (Martin and Thomas, 2011). Secondary forests emerge following natural or human disturbances, such as clearing, selective logging, introduction of invasive species, storms or wild-fires. Forest succession is a natural response to these disturbances and occurs through many speed, direction and species composition, depending on environment conditions (Lugo, 2009).

The evolution of the forest succession typically results in substantial increases in aboveground biomass (Brown and Lugo, 1990; Vieira *et al.*, 2003). Thereby, spatial and temporal changes in aboveground biomass (AGB) can be useful indicator of the velocity and direction of the forest succession because it reflects the tree growth, the increased structural complexity and primary production. Moreover, the amount of AGB can help to understand how forest structure is related to the natural environmental conditions (Saatchi *et al.*, 2007; Asner *et al.*, 2009a) and global carbon cycle (Grace, 2004).

The use of continuous forest metrics obtained using remote sensing (RS) data - e.g. aboveground biomass, tree diameter, canopy height, and canopy closure - enable improved characterization of the forest (Kalacska *et al.*, 2007), and allow the identification of ecological patterns behind land cover dynamics (Chambers *et al.*, 2007). However, challenges exist to estimating biophysical data via available remote sensing technologies, such as optical, radar and LiDAR data, which form the main tools capable of estimating forest AGB (Foody *et al.*, 2003; Saatchi *et al.*, 2007; Wang and Qi, 2008; Hall *et al.*, 2011). One issue is due to the varying spatial, temporal, radiometric and spectral resolutions unique

to each sensor system, resulting in different advantages and disadvantages to AGB estimation (Lu, 2006; Eisfelder *et al.*, 2012).

The use of estimated forest biomass in ecology depends on the cost-benefit relationship that includes image accessibility, availability of image processing techniques and data confidence. The available literature provides an overall view of RS on forest biomass estimation (Lu, 2006) and evaluates specific sensors and techniques (Hall *et al.* 2011). However, an integrated effectiveness evaluation of how the estimated AGB with RS data can be used to study the evolution of the forest succession and the secondary forest characteristics that interfere on the biomass estimation are missing. Therefore, there is a need for a critical review covering the advantages and limitations of the use of remotely sensed AGB in the evaluation of drivers and paths of the forest succession. The objectives of this review are: (a) to discuss subtle characteristics of secondary forests that challenge the use of remotely sensed AGB estimations in forest succession studies; (b) to summarize the most frequent ecological inferences discussed, and methods used, in the literature; and (c) to evaluate the implications of methodological and technological issues in the AGB estimation. We first analyze the potential use of remotely sensed AGB estimations as an ecological variable and then discuss the implications for studies of forest succession. We then summarize the ecological issues mentioned in, and the methodological characteristics of, the selected studies. We conclude with a discussion of the implications of the findings and highlight opportunities for future investigation.

2 – Review methodology

Relevant journal articles were found using key-word searches in the Web of Science Database (accessed on Jun. 2012) and by looking through the reference lists of previous narrative reviews (Lu, 2006; Chambers *et al.*, 2007; Hall *et al.*, 2011). All searches included the words “tropical forest,” “aboveground biomass” and “remote sensing” (or “sensed”). The following combinations of search terms were also used: “forest regrowth,” “temporal,” and

“forest succession”. To reach the stated objectives, we selected studies using the following criteria: (a) the search words had to be reported either in the title, abstract, author keywords or plus keywords; and (b) the aboveground biomass estimation had to be performed using biophysical structure (i.e., length, diameter, crown size) and remote sensing data. Our final database selected by the keyword searches consisted of 96 articles, of which 46 met all of the defined criteria and directly or indirectly discuss about forest succession patterns and processes. The total database (i.e. 96 articles) was used to identify the main ecological questions dealt with in the literature. The studies selected by our literature search discussed different ecological problems, including biological invasion, carbon sources and sinks, conservation status, habitat suitability, technical management comparisons, and biomass map elaboration (Table 1). These subjects were discussed in the present review because each is closely related to the forest succession process.

3 – Estimated aboveground biomass as a variable in forest succession studies

The forest succession is based on the principle that a disturbed forest patch regenerates into a mature condition (Chazdon *et al.*, 2007). However, the opposite way, from mature to initial forest stages, may also occur due to environmental conditions and disturbance (Groeneveld *et al.*, 2009; Santos *et al.*, 2008; Tabarelli *et al.*, 2008). Both directions of the forest changes result in continuous modifications in species composition and biophysical features. Successively, there is a replacement of species, tree growth and local environmental changes. Thereby, it is common to investigate how fast is the velocity of the forest regeneration, how invasive species change the regrowth tendency, what the main environmental features determining the direction of the forest succession, or what is the level of the carbon storage in different forest stages.

Table 1: Major issues discussed in the reviewed references and the information derived from the AGB estimation by using remote sensed data.

Topic	Information derived	Author, date
Forest regrowth	<ul style="list-style-type: none"> - Identifying forest regenerating processes using temporal AGB comparison - Forest structure and AGB changing across forest successional gradient 	Santos <i>et al.</i> (2003); Naughton-Treves (2004); Clark <i>et al.</i> (2004); Hoekman and Quinones (2000); Arroyo-Mora <i>et al.</i> (2005); Kellner <i>et al.</i> (2009); Wijaya <i>et al.</i> (2010); Li <i>et al.</i> (2010).
Human impact on forest biomass	<ul style="list-style-type: none"> - AGB differences due to disturbance regimes - Effect of invasive tree species on the stored AGB and forest structure 	Clark <i>et al.</i> (2004); Bitencourt <i>et al.</i> (2007); Tangki and Chappell (2008); Köhler and Huth (2010); Asner <i>et al.</i> (2010a).
Forest responses to ecological conditions	<ul style="list-style-type: none"> - AGB differences between vegetation physiognomies - Forest structure differences related to topo-edaphic gradients, climatic conditions or past land-use 	Santos <i>et al.</i> (2003); Drake <i>et al.</i> (2003); Saatchi <i>et al.</i> (2007); Broadbent <i>et al.</i> (2008); Asner <i>et al.</i> (2009a); Anaya <i>et al.</i> (2009).
Carbon sink, source and storage	<ul style="list-style-type: none"> - Carbon sequestration - Carbon amount before specific human impact - Identifying management action that can improve carbon storage 	Coomes <i>et al.</i> (2002); Hurtt <i>et al.</i> (2004); Naughton-Treves (2004); Saatchi <i>et al.</i> (2007); Helmer <i>et al.</i> (2009); Asner <i>et al.</i> (2010a); Köhler and Huth (2010); Morel <i>et al.</i> (2011); Descoux <i>et al.</i> (2011); Eckert <i>et al.</i> (2011); Ryan <i>et al.</i> (2012).
Modeling evaluation	<ul style="list-style-type: none"> - Test modeling approach - Image processing techniques - Influence of different spatial scale 	Foody <i>et al.</i> (2001); Foody <i>et al.</i> (2003); Lu <i>et al.</i> (2004); Proisy <i>et al.</i> (2007); Narvaes <i>et al.</i> (2007); Simard <i>et al.</i> (2008); Wang and Qi (2008); Helmer <i>et al.</i> (2009); Köhler and Huth (2010); Ponzoni <i>et al.</i> (2010); Li <i>et al.</i> (2010); Wijaya <i>et al.</i> (2010); Antonarakis <i>et al.</i> (2011); Nichol and Sarker (2011); Sarker and Nichol (2011); Ploton <i>et al.</i> (2012); Asner <i>et al.</i> (2012).
Sensor evaluation	<ul style="list-style-type: none"> - Test the performance of specific satellite data to estimate biomass and forest structure - Test the AGB accuracy between successional stage - Testing performance of specific satellite data to temporal comparison 	Foody and Curran (1994); Foody <i>et al.</i> (1997); Boyd <i>et al.</i> (1999); Hoekman and Quinones (2000); Salas <i>et al.</i> (2002); Santos <i>et al.</i> (2003); Clark <i>et al.</i> (2004); Hurtt <i>et al.</i> (2004); Okuda <i>et al.</i> (2004); Lu <i>et al.</i> (2004); Neeff <i>et al.</i> (2005); Proisy <i>et al.</i> (2007); Ponzoni <i>et al.</i> (2010); Angel Castillo-Santiago <i>et al.</i> (2010); Clark <i>et al.</i> (2011); Dolan <i>et al.</i> (2011); Sarker and Nichol (2011); Sarker <i>et al.</i> (2012).

Historically, these questions have been addressed by ground-based surveys, which are frequently sparsely sampled, inventoried at a small scale and time consuming (Clark *et al.*, 2004). RS technology adds new possibilities for analysis, allowing obtain data from inaccessible areas using satellite images, which can reduce biases caused by non-random plot locations.

Although important specie replacement occurs during the forest succession, in the present review we emphasize only on forest biophysical changes. Specifically, we evaluate how the estimated AGB by RS data can be used as a variable to identify drivers and directions of the forest succession and regrowth (Figure 1). The AGB was chosen because it integrates, in unique value, important forest structure information, such as tree height, diameter, number of tree by area and wood density.

Figure. 1: Climate, soil and human activities determine the forest stand structure and the forest regrowth pattern. The estimated aboveground biomass (AGB) may be used as a variable to answer ecological issues, such as forest responses to environmental conditions, habitat suitability, carbon storage and conservation in managed areas (Adapted from Baraloto *et al.*, 2011).

3.1 – Dynamics of AGB during forest regrowth from field and RS

In tropical forests, young fallows show biomass increases ranging from 1 to 15 Mg ha⁻¹ yr⁻¹ after short-term shifting cultivation (Uhl *et al.*, 1988; Brown and Lugo, 1990; Naughton-Treves, 2004; Helmer *et al.*, 2009). A mean biomass increment of 5.3 Mg ha⁻¹ yr⁻¹

has been documented in Atlantic rain forest over a 22-year study of undisturbed forest plots (Rolim *et al.*, 2004). Thus, secondary forests can rapidly grow up to 100 Mg ha⁻¹ of AGB or less than 20 Mg ha⁻¹ within 20 years after land abandonment. It depends on the propagule availability, vegetation type, environmental conditions, site productivity, intensity of the past land use, or human intervention (Swanson *et al.* 2011). In tropical forest regrowth, leaf AGB tends to increase for 20 years and wood AGB increases for 40 years before stabilizing (Brown and Lugo, 1990). These time periods seem short when compared to some modeling estimations and field observations that have indicated that the tropical forest needs approximately 80-160 years to reach the mature stage (90% of species) (Guariguata and Ostertag, 2001), although Liebsch *et al.* (2008) found an increase of approximately 57% in species richness over 25 years of forest regrowth in the Brazilian Atlantic Forest. During regrowth, the species richness and the abundance of fauna also increase rapidly and can recover in the first 10-20 years for animals that are not dependent on late-stage plant species (Bowen *et al.*, 2007).

The challenge is to obtain reliable estimates of AGB associated with regrowth using temporal remotely sensed data. Although landscape scale land cover dynamics have been accurately assessed through RS using simple classification schemes, such as forest/non forest (e.g., Almeyda Zambrano *et al.* 2010), the study of forest regrowth using continuous variables, such as AGB, can provide new perspectives on regeneration patterns. The ability to track AGB through time enables the assessments of the directional changes in forest dynamics (Chambers *et al.*, 2007). Although limitations to RS estimation of temporal variation in AGB exist, such as found by Wijaya *et al.* (2010) who showed that they overestimated forest regrowth rates as a result of forest fires and a severe El Niño drought before the image dates and uncorrected atmospheric effects, a growing number of studies are developing and implementing methodological techniques to minimize such uncertainties (Kellner *et al.*, 2009; Hudak *et al.*, 2012; Ryan *et al.*, 2012; Antonarakis *et al.*, 2011).

The spatial and temporal evaluation of forest regrowth patterns is also an important issue. Areas belonging to the same region may show different forest area increase as a consequence of differences in human demography and industrialization (Baptista and Rudel, 2006; Baptista, 2008). Moreover, the losses (by degradation) and accumulations (by forests regrowth) of biomass may change without a change in forest area (Houghton, 2005). The structure and change dynamics of an old-growth tropical forest were studied by Kellner *et al.* (2009). In 8.5 years, the authors found an equal number of positive and negative transitions of mean canopy height estimated by using LiDAR data, indicating a steady-state dynamics of disturbance and regeneration. Therefore, unknown tendencies in forest regrowth patterns associated with AGB changes can appear at different time and spatial ranges of analysis.

Forest regrowth has also been identified in remote sensed studies by using forest age classes (Helmer *et al.*, 2009; Liu *et al.*, 2008) or successional stand classes (Neeff *et al.*, 2006; Sirén and Brondizio, 2009). However, it is common for one forest age class to exhibit different structural features due to the soil and geographic features or land use history (Vieira *et al.*, 2003). In addition, forest age or successional stand information is not always available for some forest areas (Liu *et al.*, 2008).

3.2 –*Natural and anthropogenic disturbances on forest AGB*

Changes on the natural course of the forest regrowth and succession occur due to intentional fire, selective logged and with the introduction of invasive species. The forest responses to natural disturbances (i.e. storms, fire) are also a feasible use of the estimated AGB data (Dolan *et al.*, 2011). These natural and human disturbance factors may reshape the biophysical structure of the forest or reorder the plant community. Both kind of disturbances can generate AGB dissimilarity among forest patches. Some of the reviewed studies evaluated spatial and temporal changes of tree biomass in logged forests under different management techniques. Tangki and Chappell (2008) demonstrated that high-lead harvesting techniques resulted in smaller remaining tree biomasses than logging using tractor skidders.

The authors explained that the AGB differences are related to the higher levels of collateral damage caused during high-lead harvesting. In other cases, logged areas exhibited lower mean maximum crown size diameters than old growth forests (Clark *et al.*, 2004). Aerial photographs revealed that tree height/diameter allometric relationships exhibit regression slope differences between logged and old growth forests (Okuda *et al.*, 2004).

The impacts of tree species invasion on forest structures and AGB is also well studied, and particularly in Hawaii, USA. Tree invasive species can rapidly spread through seeds or vegetative propagation and show opportunistic behaviors (Busby *et al.*, 2010). This is expected to lead to changes in overall forest AGBs. Observing forest structure using LiDAR data (Asner *et al.*, 2010a), it was found that invasion by the tree *Morella faya* alters the three-dimensional structure of the rainforests, such as the mean tree height, but not the total amount of AGB at the landscape level. Contrary, the proliferation of tree species *Psidium cattleianum* and *Ficus rubiginosa* corresponded to decreases of 19-38% in tropical forest AGB (Asner *et al.*, 2009a).

3.3 – Forest responses to environmental conditions

Environmental conditions and resource availability can also affect primary net production (Clark *et al.*, 2001) and, consequently, AGB changes throughout forest succession. Differences in the spatial and temporal distributions of precipitation across bioclimatic zones constrain forest AGB in some locations and were found to be an important ecological issue discussed in the reviewed literature. The increase in the number of dry months produced a reduction in forest AGB, showing the influence of net water deficits in the forest structure at regional (Drake *et al.*, 2003) to continental scales (Saatchi *et al.*, 2007). In a study by Asner *et al.* (2009a) using airborne LiDAR data, biomass declined 53-84% in areas with increasing elevation, due to changes in temperature and humidity. Contrary, Alves *et al.* (2010) found AGB increment with elevation increase in the Brazilian Atlantic coast. All

these examples demonstrate how environmental conditions can modulate spatial and temporal patterns of forest AGB.

Another common theme in the literature focuses on spatial distribution of biomass as related to differences among forest types. Biomes or vegetation physiognomies are determined by environmental and climatic conditions. Wang and Qi (2008) reported RS AGB differences between Dry Dipterocarp Forests, Mixed Deciduous Forests and Tropical Evergreen Forests. These results illustrate the potential use of RS AGB data to distinguish between vegetation types. However, Saatchi *et al.* (2007) found that RS AGB data from Amazon forest was not a useful tool for distinguishing between vegetation types due to the low correlation between forest biomass and vegetation types in this biome. Asner *et al.* (2010b) integrated airborne LiDAR with maps of ecosystem types and found significant differences related to forest types and geologic substrate, allowing them to scale up the detailed LiDAR measurements to a large portion of the Southern Peruvian Amazon. Vieira *et al.* (2003) and Saatchi *et al.* (2007), however, found that AGB variations in tropical forests were more due to differences in soil type and land use history than forest types (Vieira *et al.*, 2003; Saatchi *et al.* 2007). Thereby, the relationship between estimated AGB and forest succession patterns need to be interpreted considering specific characteristics of forest types and the influence of environmental conditions among different scales of analyses.

3.4 – Carbon source, sink and storage

The spatial and temporal changes of AGB during the forest succession are controlled by a conjunct of environmental, biological and human factors, as seen until now. The observed forest AGB can be directly related to tree carbon storage. Dry biomass is expected to contain approximately 50% carbon (Brown and Lugo, 1982, Martin and Thomas, 2011). The relationship between AGB and carbon opens up a wide range of integrated discussions of the use of forest biomass for carbon monitoring (IPCC, 2006; IPCC, 2010). Brazil, the Democratic Republic of Congo, and Indonesia have the highest carbon stocks and the largest

tropical forest areas, indicating that great effort should be expended in the further verification and monitoring of data in these countries (Saatchi *et al.*, 2011a; FAO, 2011).

The effect of the increase in atmospheric carbon concentration on climate change is the flagship topic for the study and implementation of environmental carbon sinks as a result of the forest succession. The concept of carbon sinks has been criticized because of estimation biases and the difficulties associated with their quantification and verification using the available technology (Freedman *et al.*, 2009). The difficulty to measuring changes in biomass and the lack of spatially explicit data are the main cause of variation among carbon estimates at the same area (Houghton, 2005). To overcome these limitations, Hall *et al.* (2011) proposed a new orbital mission capable of estimating forest carbon storage around the world (see topic 4.1.1 for detail).

3.5 - *Habitat suitability*

Forest structural complexity can affect animal species distributions and abundance patterns (Heindl and Winkler, 2003). Structural attributes and micro-climatic conditions change during the forest regrowth process, which can determine habitat suitability for some species (Bowen *et al.*, 2007). A good relation of habitat heterogeneity and species diversity depends on the taxonomic group under study, how the animal guild studied perceives the vegetation structure, and the spatial resolution of the observation (Tews *et al.*, 2004). Biophysical forest characteristics obtained through RS data can generate continuum models related to ecological gradients and can be used to produce habitat suitability models (Fischer and Lindemayer, 2006).

Gradual changes in RS AGB and forest structure through space and time assessed by optical, radar or LiDAR data have also been used to investigate the relationship between habitat heterogeneity and species diversity. Kalacska *et al.* (2007) obtained a suitable RS model to estimate Shannon index in a tropical forest. However, the authors noted that remotely sensed data focusing on the canopy surface (i.e., surface reflection measured by

Hyperion) might be inappropriate for assessing relationships between sub-canopy elements, such as understory species richness. Even though the relationship between species diversity and habitat suitability has been widely documented in field-based research, the empirical knowledge of this relation may be seriously affected by the lack of information over a broad range of environmental conditions (Tews *et al.*, 2004). Such problems demonstrate the necessity of large-scale studies related to habitat suitability and the need to understand how RS data interact with field-based variables.

4 – Biophysical measurement and modeling

Having reviewed the use and interpretation of AGB as an ecological variable, the review now shifts focus to the implications of methodological and technological issues on AGB estimation. Modeling AGB depends on successful implementation of three main stages, each having particular challenges to address: (a) the remote sensed source of data; (b) the field data; and (c), the modeling approach selection (Figure 2). Due to the large diversity of data sources and modeling approaches for the modeling biomass, we focused on information that determines the interpretation of forest succession process and patterns.

		Source of variability	Challenges
Satellite survey		Resolutions: - Spectral - Radiometric - Spatial - Temporal	- Temporal and spatial availability - Financial grants - Know-how
Field survey		Ground truth: - Physiognomies - Spatial and temporal heterogeneity	- Accessibility (topography, roads, complex forest structure) - Logistic (permissions) - Time - Financial grants
Modeling approaches		Modeling: - Allometric equations - Model inversion - Uncertainty	- Availability of allometric equation from destructive surveys - Sufficient sampling - Know-how

Figure 2: Source of variability in the results and challenges related to each stage of the modeling biomass.

4.1 – Data Sources

4.1.1 – Remote sensed data

Selection of an appropriate source of data requires first the identification for the ecological question being asked and identification of the limitations and advantages of each sensor. The choice of the source of data to analyse the forest succession need to be linked to two important information, the vegetation structure and species composition. Overall, the combination or fusion of optical and radar data have the potential to achieve the highest accuracies in the estimated AGB (Kuplich, 2006; Zolkos *et al.*, 2013). Optical data can be used to improve the accuracy of radar data (Saatchi *et al.*, 2007), for example, by removing leaf backscatter and compensating leaf attenuation to woody structures in each pixel (Wang and Qi, 2008). The radar data (for example, JERS-1 images) may be especially helpful as the microwaves are independent of cloud cover, a frequent problem in tropical forests. Although

the trunk and branch biomass estimations coming from radar are better than the optical data estimations, the response cannot be always the same in terrains with steeper slopes (Lu, 2006).

Other data sources used in the studies evaluated include the Hyperion satellite sensor and aircraft based HYDICE sensor, with high spectral (220 and 210 narrow bands, respectively) and radiometric resolutions. Whereas Landsat has 8 bit resolution with 256 information levels, Hyperion data has 16 bits with 65,536 information levels ranging from data range from ~ 0.4 to $2.5 \mu\text{m}$ (Pearlman *et al.*, 2001). The greater spectral resolution provided by Hyperion can result in improved sensor capabilities to measure smaller variations in reflected energy (Legleiter *et al.*, 2002; Thenkabail *et al.*, 2004), which can be related to forest biomass or phytochemical characteristics of the canopy. The capacity of hyper spectral sensors to differentiate tree phytochemical features is the information needed to be link with forest structural data in the forest succession studies, because the canopy chemistry can reflect the species composition of the vegetation. Some research initiatives have achieved important success to obtain, at the same time, RS data from forest structure and species composition, merging LiDAR (tree height) and hyperspectral (phytochemical) data (Asner *et al.*, 2012b; Féret and Asner, 2012). These researches indicate an important direction to be focused on subsequent studies about the direction and velocity of the forest succession.

LiDAR systems can be used to obtain both top of canopy and within canopy structural information as some systems can have effective signal penetration through the forest canopy, resulting in 3D vegetation structure data (Imhoff, 1995, Drake, 2003) with spatial resolution varying according to the system design and flight altitude above the study area. LiDAR is now considered to be the state of the art for remote sensing based biomass estimation, but has significant disadvantages related to the high-cost per area, lack of historical data for temporal analysis, and the unavailability of large-scale datasets making regional or global AGB

estimation with airborne LiDAR unfeasible (Anaya *et al.*, 2009; Saatchi *et al.*, 2011a). To mitigate this problem, there is a need for a satellite based platform providing global LiDAR data optimized for AGB estimation with errors less than 10 to 25 Mg C ha⁻¹ (Hall *et al.*, 2011).

The sensors used in the reviewed studies mainly differed in cost and temporal, spatial, spectral and radiometric resolutions (Table 2). The widespread use of Landsat TM data may be attributed to the low cost of this data. Despite this, the main limitation of the Landsat images is the reflectance saturation at higher biomass values (Lu, 2006). However, the longer time span of available information (since 1984) is an advantage of Landsat data that can play an important role in temporal forest regrowth analyses.

Multi-temporal imagery can be an important source of data for the study of forest regrowth patterns, but the data processing should account for atmospheric corrections and phenological effects. Atmospheric conditions can influence optical RS data through two processes: the absorption and the scatter of solar radiance (Vermonte *et al.*, 1997). The main problem is that images from different dates were acquired under different atmospheric conditions, and pre-processing analyses needs to accurately correct for these differences (Latorre *et al.*, 2002). The comparison of multiple images from different months to monitor successional changes also needs to consider signal effect resulting from phenologic variations in the canopy. Seasonal changes in solar zenith angle, variations in the amount of leaves in the canopy and the growth of understory vegetation are the main features that can confound remotely sensed signals (Song and Woodcock, 2003).

Table 2 – Remote sense data used on the reviewed studies.

Sensor	Data used	Spatial Resolution	Cost	Nr. case studies
LANDSAT / MSS, TM & ETM+	6 optical bands	30 m	Low	10
USGS / LIDAR	Airborne laser altimeter	1.2 – 25 m	Very High	6
ALOS Palsar/AVNIR-2	Radar L band and 4 optical bands	4.8m to 9.6m	Medium	5
AIRSAR*	Radar X, C, L and P-band	1.5 – 10 m	High	5
IKONOS / IKONOS	4 optical bands	4 m	High	4
SAR/JERS-1	7 optical bands and radar L band	18 to 24 m	Low	4
SPOT-5/HRS	5 optical bands	2.5 to 5m	High	3
Terra / MODIS	7 optical bands	250 to 500 m	Low	2
GLAS/ICESat	Laser altimeter satellite	0.75 to 75m	High	2
NOAA/AVHRR	5 optical bands	1.1 Km	Low	2
Quickbird / Quickbird	4 optical bands	2.4 m	High	1
EO-1 / Hyperion	220 optical bands	30 m	Very High	1
NASA / QuikSCAT	Radar L and P bands	12 m	Medium	1
Aerial photographs	RGB true color composite	-	High	1
SIR-C	X, C and L bands	15 to 25m	Medium	1
CHRIS / PROBA	62 optical bands	18 m	Medium	1
VHR Google	RGB true color composite	1 m	Low	1
HYDICE**	210 optical bands	0.75 to 3.75 m	Very High	1

*AIRSAR: airborne synthetic-aperture radar; **HYDICE: Hyperspectral Digital Imagery Collection Experiment

4.1.2 – *Ground truth*

The reviewed studies obtained ground truth field data from plots or through the point quadrant method. The total sampled area ranged from 1.5 to 272 ha, but in 70% of the studies the area ranged from 1 ha to 9.5 ha. Access difficulties may create restrictions to sampling of larger areas. Studies with small sampling areas tended to overestimate AGB per hectare, but this tendency is not always significant (Brown and Lugo, 1992). Even so, the ground truthing of only small areas may result in site-specific models and limits the transferability of the model to other areas (Foody *et al.*, 2003). To minimize this condition some studies have used large field databases merging data from different regions (Saatchi *et al.* 2007; Anaya *et al.*, 2009; Asner *et al.*, 2012).

The suitability of the method depends on the scale of the study area and the structural heterogeneity of the forest (Luckman *et al.*, 1997; Houghton *et al.*, 2001). The greater the sampling spatial scale, the greater probability of having good representation of forest structural heterogeneity in the region, indicating that a broad sample area may be required. Moreover, there is a need for a minimum knowledge about the spatial distribution of the forest structure studied (Tomppo *et al.*, 2008) and the local influence of the topography and soil on the AGB. Tropical trees tend to exhibit an aggregation pattern (Hubbell, 1979) and high variability within short spatial distances in forest structure and biomass (Saatchi *et al.*, 2011b), resulting in a complex mosaic that can be difficult to fully sample. The use of plots greater than 0.1 ha has been shown to be more reliable than smaller plots, which is also related to decreased stochastic small-scale disturbances having disproportionate weighting on total measured structure and AGB (Saatchi *et al.*, 2011b). This sampling strategy maintains greater spatial overlap between ground-reference and sensor data, it captures greater forest variability and reduce edge noise from neighboring trees (Frazer *et al.*, 2011). The use of the point-centered quarter method has the advantage of evaluating forest heterogeneity at less effort and lower cost than plot-based sampling, but this method can underestimate densities

and basal areas (Lindsey *et al.*, 1958). The studies that used point-centered quarter method also showed high correlation values between field and RS data (Bitencourt *et al.*, 2007; Wang and Qi, 2008). Nevertheless, the use of this method needs to be better evaluated as a ground truth option because such a method has the potential to be used in large-scale studies with reduced fieldwork. Furthermore, a hierarchical sampling scheme of plots, quadrants and sub-quadrants can be a good way to include this complexity (Li *et al.*, 2010). Data from the smallest scale (sub-quadrant) can be treated as random draws from an unobserved quadrant and modeled to obtain uncertainty parameters for the regression of quadrant and satellite data (Wilson *et al.*, 2010).

4.2 – Statistical modeling

4.2.1 – Allometric equation to estimate field biomass

The studies reviewed used between 1 and 16 different allometric equations per study to estimate AGB. Different allometric relations between biomass and tree diameter or height are set by environmental (e.g., ground slope, climatic conditions, light level) or biological factors (King *et al.*, 2006), and can explain up to 90-95% of the ground AGB (Vieira *et al.* 2003; Burger and Delitti, 2008). Testing allometric model accuracies, Vieira *et al.* (2008) applied several allometric equations (developed by different authors) to the same diameter at breast height (DBH) and height and found a difference of 5-7% in AGB estimations, indicating a source of error dependent upon the equation choice. Another source of error in the forest AGB estimation may be the lack of information from non-arboreal sources (such as lianas, palms, tree ferns, bamboo and epiphytes), which can account for more than 10% of the AGB in Atlantic Forest areas (Vieira *et al.* 2008).

The choice of the equation used to estimate AGB may depend on the height and DBH range, and on the species composition of the forest studied. Attention to these factors may improve the suitability of the biomass estimation using allometric equations (Nelson *et al.*,

1999; Li *et al.*, 2010). Another option would be to include wood density in the biomass estimation, providing a more accurate representation of tree biomass than those relying only on DBH and height (Broadbent *et al.*, 2008). When species-level data are not available, a mean wood density by forest type, family, or genus can be used (Alves *et al.*, 2010).

4.2.2 – *Remotely sensed biomass estimation by model inversion*

The main statistical tool used in the studies to relate field and RS data was simple linear and non-linear regression. Modeled biomass values from tropical forests can display non-linear trends in the residuals, indicating the use of non-linear models (Liu *et al.*, 2008). Li *et al.* (2010) obtained better adjusted R-squared and Mean Squared Error values using non-linear models than linear models and presented a clear framework to develop a non-linear biomass model for tropical forests. The use of neural networks is an alternative that can play a significant role in obtaining better accuracy (Ingram *et al.*, 2005). However, neural networks' models have a substantial subjective component and can be relatively poor for semantically relating field and remotely sensed data (Foody *et al.* 2001). Generalized Linear Models (GLM) have also been used to analyze the suitability of AGB models using Akaike Information Criterion and R-squared values to evaluate model performances (Kajisa *et al.*, 2009). GLM models allow us to explore combinations of factors, covariates, and interactions among variables through a process called iteratively reweighted least squares. This overcomes the basic problem related to regression models that is the change in the variance as a consequence of the transformation of the data to attain normality (Bolker, 2008).

4.3 – *Uncertainty*

In the modeling context, uncertainty is the lack of knowledge of the true values of a variable, which can be estimated by the range and likelihood of possible values (IPCC, 2006). The overall uncertainty in AGB estimation using RS is directly related to the relationship between a set of potential errors coming from processing satellite data (Topic 4.1.1), field

data (Topic 4.1.2), statistical modeling (Topic 4.2), and the ecological variables studied. Beyond the uncertainty from each variable, the errors can come from the interaction among them, for example in the conflict of scale between satellite and field data samples. The challenge is to balance how the errors influence the ecological data interpretation and how the errors from each modeling step influence the overall error.

Most studies considered were mainly performed in flat forest areas. In optical images, ground slope can shade areas, resulting in decreased reflectance values compared to flat areas (Riaño *et al.*, 2003) and the generation of spectral differences between forests at the same successional stage (Song and Woodcock, 2003). These topographic effects can be minimized by different algorithmic corrections (Gao and Zhang, 2009), but biases may still be included in analyses.

The position errors of the sensor data can also reduce the modeling accuracy in pixel-based modeling (Song and Woodcock, 2003). Two common strategies were used to minimize this problem: the correlation of the field data with a 3×3 or 5×5 pixel window around the ground data (Foody *et al.* 2001; Kalacska *et al.*, 2007; Lefsky *et al.*, 1999) and the use of a mean radiance from a forest patch (Tangki and Chappell, 2008; Wang and Qi, 2008). These modeling can also reduce the confidence level of the model due to the high area disproportion between the field area plot (i.e. 0.09 ha) and the pixel window from, for example, the Landsat data (2.25 ha in a 5×5 window).

The root mean square error (RMSE) and determination coefficient values were widely used to compare the accuracies of the AGB estimates. The error estimate had a mean value of 41.2 Mg ha⁻¹ (SD = 29.3 Mg ha⁻¹), considering the reviewed studies that present this analysis in the results (17 studies from the 46 analyzed). Commonly, the RMSE is obtained from the comparison of model predictions with independent data. Data can be randomly separated in two groups, one to implement the model and one to check its performance. This process can be repeated many times to obtain randomized RMSE values. Finally, all values are used to

build up the overall error probability density function, which can be used to evaluate the magnitude and trend direction of the errors (IPCC, 2006).

Li *et al.* (2010) found that the AGB model might show inflated residual variances toward higher biomass values. The authors noted that the residual can be associated with the use of the same allometric equation to trees with different sizes and forest with different structure complexities. Errors in forest AGB estimation can be random or systematic (Saatchi *et al.*, 2011b). Minor AGB errors have been found in forests with low biomass (Drake *et al.*, 2003; Saatchi *et al.* 2007; Köhler *et al.*, 2010).

Despite these inherent modeling errors, biomass estimation using exclusively field data is far from easy and free of errors (Foody *et al.*, 2003). Studies based only on field information are accurate at the local scale but may fail to take into account the large spatial variability of biomass. AGB estimations using only field data over large areas showed an overall sampling error of approximately $\pm 20\%$ (Chave *et al.*, 2005; Alves *et al.*, 2010). Moreover, field-based measurements and estimates are time consuming, labor intensive, and difficult to implement in remote areas (Lu, 2006). Challenges exist in the collection of both data, the RS and field. However, the integration of these different sources of information is crucial to better estimate AGB in any site.

5 – Synthesis and further research

The biomass estimation using remote sensed data is an important source of data to analyze the forest succession, because the biomass information integrates different forest structure data, such as tree height, diameter, number of trees by area and wood density. Moreover, the estimated biomass is sensible to different forest regrowth pattern, may be determined by human and natural disturbances, and indicates the carbon amount stocked during the forest succession process. The specie replacement and the tree growth are continuum processes during the forest succession. Thereby, some concerns exist in the

exclusive use of structural forest data to define succession stages, because it excludes information about the tree specie composition. The fusion between different remote sensor data focusing on structural (Radar and LiDAR) and phytochemical (hyperspectral images) features of the canopy may minimize this problem.

Access to ground truth data from past dates and image calibration between different dates are the main difficulties in temporal AGB comparisons. Most of the selected studies merely indicated forest regrowth as a potential subject to be analyzed by AGB estimation but did not actually address the topic. In fact, there is a lack of deep interpretation of some ecological process for tropical forests based on remotely sensed forest structure estimation (Asner *et al.*, 2009a). Nevertheless, the potential for the use of remotely sensed biomass estimations in forest succession studies in tropical forests remains great, although the outstanding AGB changes occur approximately until 40 years in tropical forests. Spatial AGB distributions can also be important sources of data for forest management analysis, conservation status evaluation, carbon source, and sink investigations and the study of the relationships between environmental conditions and forest structures. We suggest that further research on forest succession patterns should be carried out focusing on how human and environmental features determine AGB increases or decreases at different landscape scales.

In this study, we have reviewed the advantages and disadvantages of the use of forest biomass estimation by using remotely sensed data in forest succession analysis. Our review indicates that accuracy and precision assessment are the most important challenges related to these issues. The uncertainty estimates need to be robust and transparent, due to the current importance for decision makers (IPCC, 2010). In addition, the evaluation of the studies reviewed here indicates that errors in AGB estimations can in some cases be the same as annual AGB changes by regrowth process, making AGB comparisons on a short time scale unfeasible using imprecise or biased data. However, long time scale lag comparisons are still possible if attention is paid to spectral variations between satellite images related to

atmospheric conditions and satellite signal degradation over time. Hall *et al.* (2011) highlighted the importance of a new space mission with a technology able to obtain biophysical forest estimates with lower errors in short time scale comparisons.

A reliable AGB estimation depends on the sensor type, processing strategy and forest characteristics. In focusing attention only on the RS data process, we may fail to catch the ecological patterns analyzed. Our results suggest that sampling choices depend on intrinsic forest features and sources of noise related, for example, to topographic characteristics. In addition, we discussed some positive and negative features of each sensor for obtaining AGB estimations. The choice of data source depends on trade-offs between advantages and disadvantages of methodological and technological features.

When making a modeling choice, attention must be paid to different potential sources of bias in the biomass regression models, including: (a) sample size; (b) accuracy of the allometric equations; (c) image calibration; (d) the methodology used for temporal adjustments between the sampled biomass data and satellite observations; (e) the multicollinearity of the polynomial model (Li *et al.*, 2010); (f) the fact that 30-50% of the forest biomass is hidden by emergent trees (Broadbent *et al.*, 2008); (g) the increased number of lianas in the intermediate successional stage (Kalacska *et al.* 2007); (h) topography; and (i) the past land use context in the study of forest regrowth dynamics. The possibility that one or more of these sources of bias shows us that attention needs to be paid to sampling, statistical and RS data process choices and specific forest features in the modeling process.

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