Toward an integrated monitoring framework to assess the effects of tropical forest degradation and recovery on carbon stocks and biodiversity

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First published: 21 September 2015

https://doi.org/10.1111/gcb.13087

Abstract

Tropical forests harbor a significant portion of global biodiversity and are a critical component of the climate system. Reducing deforestation and forest degradation contributes to global climate-change mitigation efforts, yet emissions and removals from forest dynamics are still poorly quantified. We reviewed the main challenges to estimate changes in carbon stocks and biodiversity due to degradation and recovery of tropical forests, focusing on three main areas: (1) the combination of field surveys and remote sensing; (2) evaluation of biodiversity and carbon values under a unified strategy; and (3) research efforts needed to understand and quantify forest degradation and recovery. The improvement of models and estimates of changes of forest carbon can foster process-oriented monitoring of forest dynamics, including different variables and using spatially explicit algorithms that account for regional and local differences, such as variation in climate, soil, nutrient content, topography, biodiversity, disturbance history, recovery pathways, and socioeconomic factors. Generating the data for these models requires affordable large-scale remote-sensing tools associated with a robust network of field plots that can generate spatially explicit information on a range of variables through time. By combining ecosystem models, multiscale remote sensing, and networks of field plots, we will be able to evaluate forest degradation and recovery and their interactions with biodiversity and carbon cycling. Improving monitoring strategies will allow a better understanding of the role of forest dynamics in climate-change mitigation, adaptation, and carbon cycle feedbacks, thereby reducing uncertainties in models of the key processes in the carbon cycle, including their impacts on biodiversity, which are fundamental to support forest governance policies, such as Reducing Emissions from Deforestation and Forest Degradation.

Introduction

In 2010, total anthropogenic GHG emissions reached 49 (±4.5) Pg CO_2 eq. yr^{-1}, 76% of which consisted of CO_2 emissions. Agricultural, forest, and other land-use sectors (AFOLU) account for 20–25% (~10–12 PgCO_2 eq. yr^{-1}) of net anthropogenic GHG emissions, of which 4.3–5.5 Pg CO_2 eq. yr^{-1} is from forestry and other land use (FOLU) (Smith *et al*., 2014). Estimates indicate that there has been a recent decline in CO_2 emissions, largely because the rate of tropical deforestation has decreased but forest degradation is likely important but still poorly accounted for in current FOLU emissions (Smith *et al*., 2014).

Globally, forest degradation affects approximately 100 million ha of forest per year (FAO, 2006; Nabuurs *et al*., 2007). Indirect estimates of forest degradation, expressed as a percentage of emissions from deforestation, are highly variable, ranging from 5% in the humid tropics to 25–42% in tropical Asia and 132% in tropical Africa [see Houghton (2005) for a review]. Conversely, regrowth of secondary forests may remove considerable amounts of carbon from the atmosphere (Pan *et al*., 2011), and extensive areas of regrowth have been reported in the tropics (e.g., Aide *et al*., 2013a). Asner *et al*. (2010) used high resolution (0.1 ha resolution) satellite imagery to analyze 4.3 million ha in the Peruvian Amazon (1999–2009) and found that forest degradation added ≅ 47% more carbon to the atmosphere than deforestation alone and that secondary regrowth provided an 18% offset against total emissions in Peru, a high forest cover, low deforestation country. Despite some attempts to estimate carbon losses resulting from forest degradation (Achard *et al*., 2004; Berenguer *et al*., 2014), this is still a major challenge for national carbon inventories. Carbon finance schemes, such as the UN-led Reducing Emissions from Deforestation and Forest Degradation (REDD+), require accurate estimates of carbon emissions and robust monitoring and reporting of changes in carbon stocks (Andersson *et al*., 2009; UNFCCC, 2011).

Although satellite and airborne remote-sensing technologies associated with field measurements have strong potential to assess large-scale (national and global) carbon stocks (DeFries *et al*., 2007; Goetz *et al*., 2009; Saatchi *et al*., 2011; Baccini *et al*., 2012), current methods and data cannot deliver the desired precision to assess and monitor forest stocks and changes due to forest degradation and regrowth (Asner *et al*., 2009; GOFC-GOLD, 2013). In fact, estimates of CO_2 emissions related to FOLU have uncertainties of the order of 50% (IPCC, 2014). Quantifying forest degradation and regrowth at large scales remains a major constraint in the implementation of REDD+ mechanisms (Aguiar *et al*., 2012; Mitchard *et al*., 2014; Ometto *et al*., 2014).

Important consequences of deforestation and forest degradation include decreases in environmental, social and economic functionalities (Nepstad *et al*., 2001; de Mendonça *et al*., 2004; Tavani *et al*., 2009), increased vulnerability to fire (Cochrane & Schulze, 1999; Nepstad *et al*., 1999; Matricardi *et al*., 2010; Alencar *et al*., 2011), and doubling of net carbon emissions from regional land-use during severe El Niño episodes and other drought years (Alencar *et al*., 2006; Chen *et al*., 2013; Aragão *et al*., 2014). Reducing deforestation and expanding secondary forests can increase forest resilience to more frequent and severe droughts, which are projected by the latest generation of climate models for some tropical forest regions, and increasing the risk from forest fires in coming decades. Thus, reducing emissions from forest degradation, not only emissions from deforestation, is essential to mitigate global climate change (Aragão & Shimabukuro, 2010) and its impacts on forests and other ecosystems.

Forest resilience, and therefore its ability to retain and accumulate carbon, depends on the composition and key functional relationships between species. Anthropogenic disturbance degrades forests by reducing taxonomic and functional diversity and ecological redundancy and preventing recovery and destabilizing forest ecosystems (Thompson *et al*., 2009). Forest biodiversity conservation is a critical component in the development and implementation of REDD+ (Díaz *et al*., 2009; Convention on Biological Diversity, 2011). REDD+ projects have strong potential to conserve biodiversity and ecosystem services (Gardner *et al*., 2012). Biodiversity conservation is often assumed to be a cobenefit of activities that reduce forest carbon degradation (Waldon *et al*., 2011), but REDD+ projects can have detrimental impacts on biodiversity if low-carbon, high-biodiversity forests are replaced with high-carbon, low-biodiversity land uses, or if protection of high-carbon forests in one area leads to degradation of areas with endemic species or high-diversity forests elsewhere. Thus, biodiversity monitoring within a REDD+ framework is necessary to ensure that impacts, beyond carbon, are positive (Harrison *et al*., 2012).

Future mitigation scenarios also rely on the central role of land-cover/land-use changes (Smith *et al*., 2014). Therefore, monitoring systems for forest dynamics represent an important interface between science and policy. To ensure that predictions of change for a given action can be reconciled with actual changes in C stocks, integrative and multiscale approaches are needed to make systems applicable for a wide range of national realities and capabilities. One option for efficient and effective monitoring of forest dynamics is wall-to-wall assessment and temporal reassessments, using short time intervals to study forest recovery and resilience. Currently, monitoring systems provide classification with well-developed land-cover and change estimates but identification of changes in carbon stocks needs to be based on more ground information.

Monitoring forest degradation and REDD+ monitoring, reporting, and verification systems can be based on two components: activity data, to assess changes in forest area over time (forest cover loss in ha per year); and emission factors, to assess changes in average carbon stocks per unit area over time (change in carbon stocks in Mg C ha^{-1}) (GOFC-GOLD, 2013). Activity data can be readily obtained from remote-sensing imagery to detect deforestation, but detecting forest degradation with these data is still a challenge. Moreover, emission-factor estimates for tropical forest deforestation and degradation are far more challenging to obtain (Plugge & Köhl, 2012). Another important issue for REDD+ and forest degradation is building appropriate reference scenarios. REDD+ requires a reliable benchmark against which emission reduction can be calculated. This benchmark, sometimes termed a baseline or reference emission scenario, refers to how much emission would occur in the absence of a project. Credits will be based on the difference between this baseline and project net removals. However, developing countries frequently lack consistent historical monitoring and land-cover data. Therefore, in assessing historical degradation, they are forced to rely strongly on remote-sensing approaches mixed with current field assessments of carbon stock changes (Herold *et al*., 2011). Given the lack of historical biomass data for appropriate benchmarks and the limited capability for monitoring degradation using remote sensing, Morales-Barquero *et al*. (2014) proposed that forest degradation is best measured against a local benchmark that represents areas of low or no degradation and sharing comparable biophysical characteristics.

Here, we review the main challenges to estimate changes both in GHG fluxes associated with carbon stocks, and biodiversity due to tropical forest degradation and regrowth. Three main points are stressed: (1) the combination of field inventories and remote sensing; (2) evaluation of biodiversity and carbon values under a unified strategy; and (3) research efforts needed to understand and quantify forest degradation and recovery. When combined, these three points can support the development and implementation of public policies that ensure tropical nations compliance to international commitments and efforts, such as those established by REDD+ national strategies.

Evaluating changes in forests: combination of field inventories and remote sensing

Forest degradation can be defined as the reduction of the capacity of a forest to provide key ecosystem services, such as carbon storage, and can be caused by natural (e.g., landslides and hurricanes) or human disturbances (e.g., selective logging and understory fires) (Parrotta *et al*., 2012). Forest degradation, therefore, implies that quantifiable forest variables, such as canopy cover, remain above the threshold used to define deforestation. However, measuring carbon-stock changes due to different degrees of forest degradation is more complex and more costly than measuring carbon loss due to deforestation. This is because, while deforestation is highly visible for broadleaf tropical forests (i.e., the complete forest cover of an area disappears), degradation can be cryptic both to remote-sensing techniques and field observation (Peres *et al*., 2006; Barlow *et al*., 2010; Berenguer *et al*., 2014). Furthermore, changes in forest structure following disturbance may not be very pronounced (Pereira *et al*., 2002). Forest responses to disturbance depend on the disturbance type, frequency, intensity, and extent, on intrinsic site characteristics (e.g., climate, soil, topography, species composition, and interactions), and on forest management (Fig. 1). Forest postdisturbance trajectories can vary widely, and this variation needs to be considered in carbon accounting exercises, including patterns of regrowth over time (e.g., spatially explicit map of secondary forest and their turnover, faunal diversity, and nutrient availability). Events that are associated with large changes in the forest C stock and areas where carbon-storage changes are greatest, such as areas undergoing deforestation, degradation, and secondary forests dynamics, should be identified, quantified, and monitored in detail, as well as their impacts on long-term changes in community and key species composition.

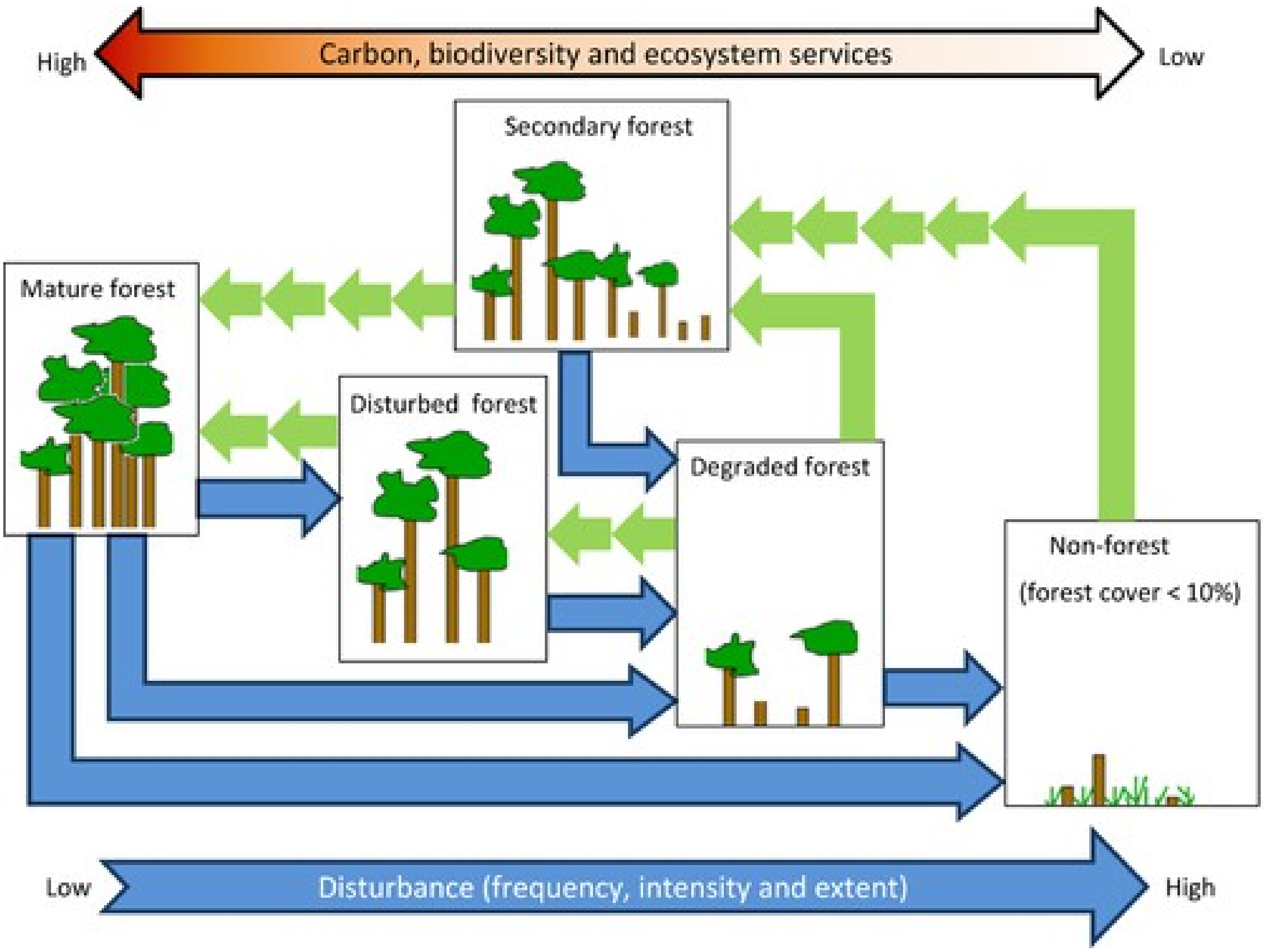

Figure 1

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Possible trajectories of forests under different levels of disturbance (intensity, frequency and extent). Blue arrows represent disturbances, and green arrows indicate regrowth of forests.

Countries can measure current rates of forest degradation through field or remote-sensing data, but a combination of the two types of data can reduce uncertainties in regional and national estimates (Asner *et al*., 2010). There is a direct relationship between an accurate and precise assessment of changes in carbon stocks and cost, with costs of measuring changes in carbon stocks increasing as both precision and landscape heterogeneity increase (IPCC, 2000). Therefore, trade-offs between measurement efforts and uncertainty should be indicated when choosing spatial scales and measuring methods in carbon accounting (Fig. 2).

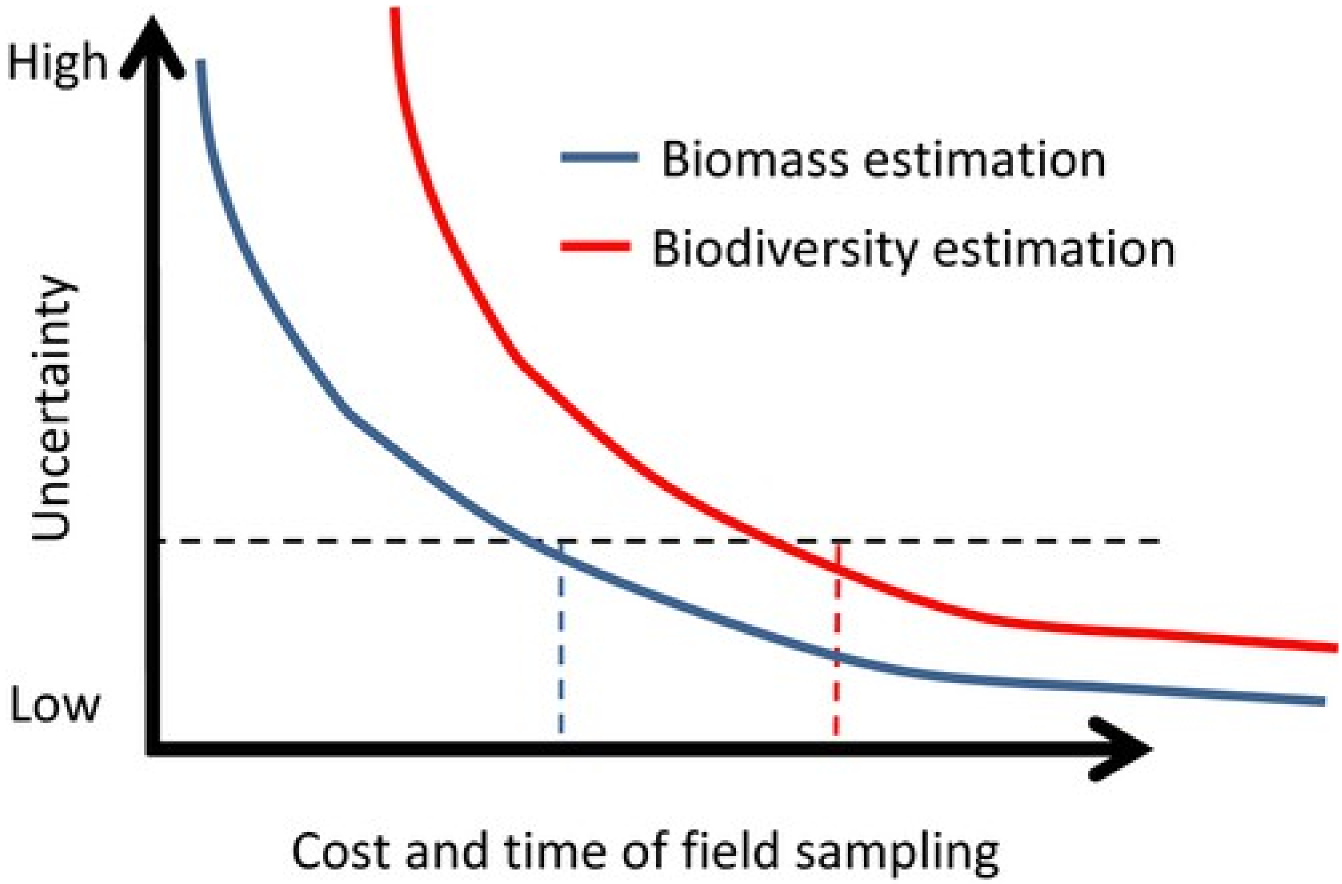

Figure 2

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Relationship between accuracy and costs and time of measuring forest carbon stocks and biodiversity.

Although field assessment and monitoring of carbon stocks are relevant for small-scale projects, they are impractical and too expensive at the national scale. Still, field assessments and monitoring of forest carbon can provide valuable information about local changes in carbon stocks due to human disturbance (Barlow *et al*., 2003; Berenguer *et al*., 2014), which may not otherwise be detected. In many cases, significant cost savings can be made by focusing on the largest stems, which store the largest amount of carbon and are highly sensitive to disturbance (E. Berenguer *et al*., unpublished results). In addition, if field-based carbon assessments and monitoring incorporate identification of plant species, they can also deliver important information about changes in species composition (Laurance *et al*., 2006), which in turn can feedback into biological safeguards of each carbon conservation project. This is particularly important in secondary forests, where failure to incorporate species identity can incur an error in aboveground carbon estimates of about 30% (E. Berenguer *et al*. unpublished results).

Remote-sensing techniques can be a cost-effective option to assess forest carbon stocks over very large areas (e.g., nation-wide). Depending on the technique used, remote sensing may provide data at regular intervals, allowing countries to frequently monitor deforestation and degradation events, as well as subsequent carbon loss (e.g., different systems used in Brazil for monitoring of the Amazon forest, such as DEGRAD, PRODES, and DETER). However, although optical sensors can be used to identify forest degradation by selective logging and wildfires, as well as to estimate the extent of affected areas, (Asner *et al*., 2005a; Souza *et al*., 2005; Herold *et al*., 2011; Morton *et al*., 2011), they can only detect changes that affect canopy properties, thus neglecting changes in the understory. Furthermore, the ability to detect changes in carbon stocks due to forest degradation varies according to the technique used, with some being more accurate than others (DeFries *et al*., 2007; Gibbs *et al*., 2007).

Thus, changes in carbon stocks resulting from forest degradation rely on a combination of field surveys (site-specific biophysical field attributes) and remote sensing. The choice of the method to monitor forest degradation depends on multiple factors, such as type of degradation, available data, capabilities and resources (Herold *et al*., 2011). Challenges associated with different methods include temporal thresholds and spatial scales and integration of field and satellite data sets (Fig. 3). Key issues to consider are which biophysical parameters should be measured and which time windows are appropriate to integrate the two approaches.

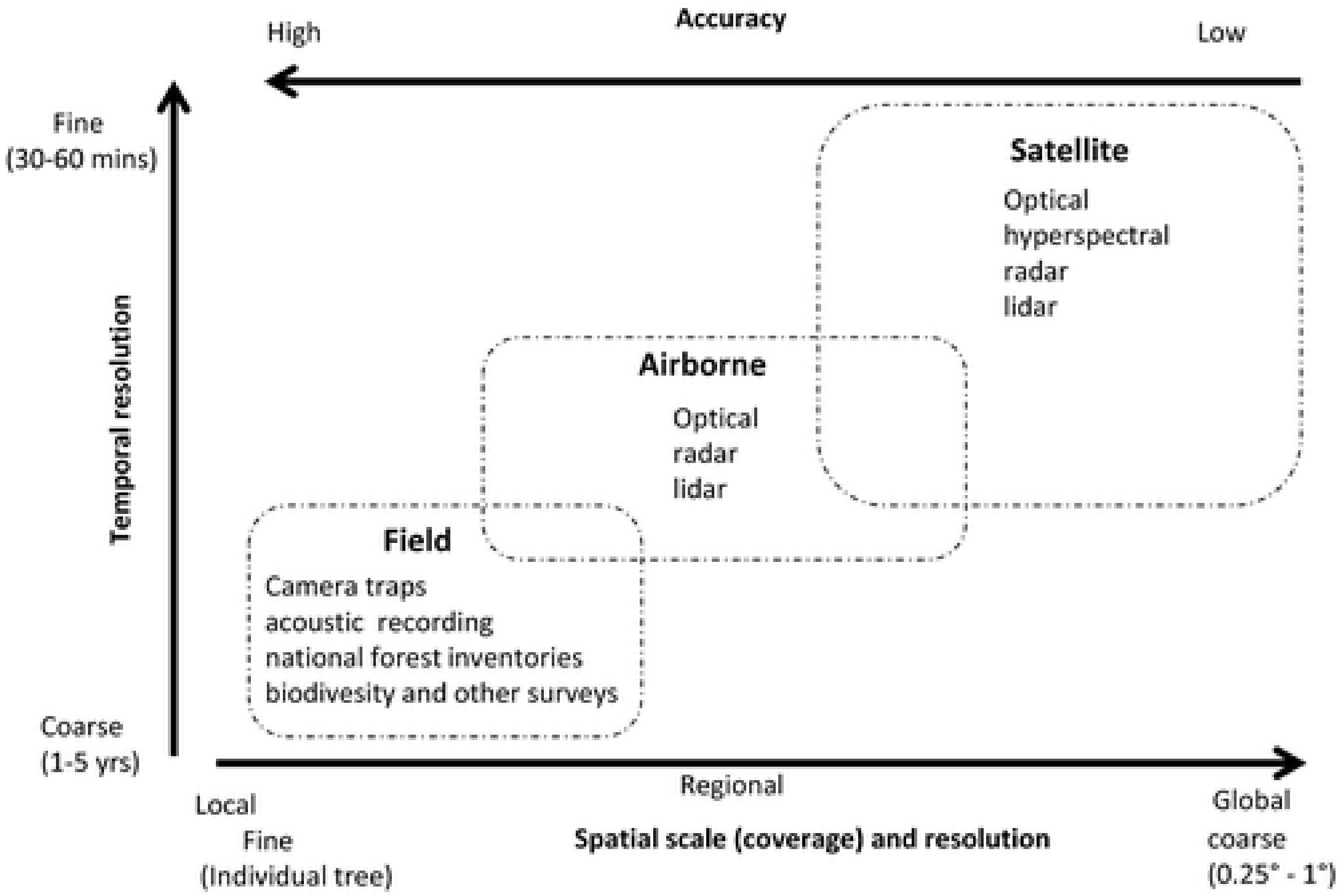

Figure 3

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Spatial scale and temporal resolution of different methods for monitoring forest carbon stocks and biodiversity.

Remote-sensing methods for monitoring carbon-stock changes and forest degradation have been extensively reviewed and discussed (Lambin, 1999; IPCC, 2003; Boyd & Danson, 2005; DeFries *et al*., 2007; Gibbs *et al*., 2007; Wertz-Kanounnikoff, 2008; Frolking *et al*., 2009; Goetz *et al*., 2009; Herold *et al*., 2011; GOFC-GOLD, 2013). Gibbs *et al*. (2007) outlined the benefits and limitations of different methods to estimate carbon-stock changes, concluding that there is no best method, and most are complementary. In fact, the formula for an effective monitoring system is consensual and seems rather simple: combining satellite (and/or airborne) remote sensing to (scale-up) allometric and statistical models, developed and based on robust field-based data sets (DeFries *et al*., 2007). Recently, this has been successfully applied in Panama and Peru, resulting in high-fidelity carbon maps for both countries (Asner *et al*., 2013, 2014). However, even though carbon dynamics in forests are far better understood than in other vegetation types (grasslands/drylands, wetlands/peat lands) (Negra & Ashton, 2010), uncertainties about forest carbon stocks are still very high. Pelletier *et al*. (2011) synthesized the key sources and associated explanations of uncertainty in the quantification of emissions from land-cover change using Panama as study case (Table 1). The combination of errors drawn from allometric equations and sampling can be as large as 20–50% of the aboveground-biomass estimate. Other factors include historical map quality, land-cover classification accuracy, the time interval between two land-cover assessments, and the fallow C. That study did not address forest degradation or soil C estimates because of the lack of robust information on these processes. Better ground observations that include long-term field studies on soil C pools, which cannot be monitored from space but are relevant, would improve emissions accounting and the understanding of forest dynamics.

Table 1. Key sources of uncertainty and their associated difference with the Reference Level for REDD+. From: Pelletier *et al*. (2011)

Sources of error	%	Explanation
Mature forest C density	54.5	No standardized methodology and error-prone allometric equations or biomass emission factors
Deforested area	2.2–19.1	Error in land-cover classification/Lack of classification accuracy assessment
Snapshot effect	19.3	Long time interval between two maps/Lack of knowledge on land-cover dynamics
Land-cover map quality (9 and 8 years)	15.6–35.2	Map based on a mosaic of satellite image from very different years Low availability of useable satellite imagery (cloud cover, long revisiting time, seasonality) Coarse-resolution imagery (e.g., MODIS or AVHRR) with more frequent revisit times would not produce accurate estimates of deforestation Lack of receiving station for Central America and Central Africa
Fallow C density	22.4	Lack of data availability for fallow land

Sources of error	%	Explanation
		Likely to affect countries where fallow occupies a significant fraction of the territory

Most methods combine remote-sensing analyses with field plots, which are limited (in number and spatial distribution) and possibly biased (Marvin *et al*., 2014; Saatchi *et al*., 2015), resulting in many divergent biomass maps in the literature (Houghton *et al*., 2001, 2009; GOFC-GOLD, 2013; Mitchard *et al*., 2014; Ometto *et al*., 2014). Estimates of aboveground carbon stocks vary by over 100% in African forests (Lewis *et al*., 2009) and by 60% in Amazonian forests (Houghton *et al*., 2000). Emission estimates calculated from land-cover change in the Amazon remain markedly divergent and are largely due to differences among biomass maps (Aguiar *et al*., 2012; Ometto *et al*., 2014). Ometto *et al*. (2014) emphasized the need for higher resolution biomass maps, and for improving ground-truth data (e.g., via field networks), and post-processing data to include variability, such as topography and soils. Uncertainty associated with regional-scale values from different sources (to quantify biomass and fluxes) is also high. Wright (2013) argued that Pan *et al*. (2011) overestimated terrestrial-carbon sinks because of incompatibility between the sources used for forest area and carbon stocks. Forest area was based on FAO's Forest Resource Assessment (FAO-FRA), which defines forest as land with trees >5 m of height and canopy cover ≥10%. However, carbon stocks were derived from plots located in tall, closed canopy forests, in which carbon stocks and changes are potentially much larger than in open forests (Wright, 2013).

Optical sensors can only detect changes that affect upper canopy properties and have limited ability to estimate C stocks and C-stock changes, especially for dense forests, because spectral indices saturate at relatively low C stocks. Estimating forest biomass requires information on tree volume and wood density. In contrast to passive optical sensors, active sensors from radar and LiDAR can provide data to estimate biomass volume, but an estimate of wood density is still needed. Large-scale estimates of forest biomass with active sensors have been hampered by costs or operational limitations. Despite these limitations, LiDAR is becoming a useful tool that scientists use to understand physical variation in tropical forests across space and time (Mascaro *et al*., 2014). Recent and future developments will increasingly allow large-scale surveys (e.g., cost reduction of airborne surveys and European Space Agency satellite LiDAR to be launched by 2020). To take full advantage of such remote-sensing developments, well-sampled and precisely located ground-truth data are needed for calibration.

National forest inventories (NFIs) often comprise a robust, large-scale (country level) and unbiased network of permanent plots and could help to provide much of the data needed for calibration for LiDAR and radar derived properties (e.g., for estimating biomass stocks and their changes). For this reason, they can help integrate remote-sensing and field data on carbon changes, especially if location of the plots is precisely recorded. For example, with approximately 2000 measuring plots, the Peru National Forest Inventory is designed as a multipurpose inventory including the state and valuation of forests, deforestation, forests degradation, carbon sequestration and emissions, biodiversity, and socioeconomic relationship of forests. Similarly, the Brazilian NFI, currently underway, will provide continuously updated estimates of forest carbon density, tree species composition, soil, and socioeconomic variables, which are based on a massive sample size (15 000 clusters with four subplots each), in a systematic and unbiased sampling design that is limited mainly by land-access issues. The Mexican NFI was based on the United States and Canada's NFIs and contains data on tree species, shrubs, and trees for every forest vegetation type. In 2009, Mexico included a soil survey with the National Forest Inventory quantifying organic soil carbon pools and biomass carbon ratios. Results are part of a national soil database.

Biomass maps should not be static but should be produced in time series, thereby capturing C-stock evolution across time as consequence of observed events (or when time series are projected, using dynamic modeling, reflecting the risks of biomass loss). Forest plots under different management regimes, environmental conditions, and disturbance trajectories are relevant for ecological studies involving forest disturbance and recovery. Building an observational network of forest plots is a primary need that requires careful planning, including landscape-level assessment, integration with initiatives currently underway, and evaluation of time intervals for temporal reassessments needed to examine recovery and resilience of forests. The coordination between detailed efforts (with more frequent and detailed sampling) and NFIs that have less detail but cover larger areas (including private lands) is highly desirable, considering information consistency.

An effective program of monitoring of forest dynamics must include the risk of fire, the fire regime, and emissions-associated environmental impacts. Fires affect large areas in the tropics (Morton *et al*., 2013) and have a wide range of effects on forest structure, carbon storage, and biodiversity (Barlow & Peres, 2008; Silveira *et al*., 2013; Oliveiras *et al*., 2014). In the Amazon, extreme droughts caused by ENSO or other climatic phenomena boost fires (Aragão *et al*., 2007) and the combined effect of drought and forest fires may turn the Amazon into a carbon-source system (Aragão *et al*., 2014; Gatti *et al*., 2014). For example, during the 1998 ENSO, forest fires affected an area twice as large as the average deforestation in that decade, generating committed emissions of 0.16 Pg C, which is comparable to the 0.2 Pg C emitted by deforestation in that period (Alencar *et al*., 2006). Forest fires react to forest structure, drought, and fragmentation, generating distinct spatial processes of degradation. Dense forests burn more in ENSO years in small patches and at lower frequencies (up to 6 times in 24 years) compared with transitional forest that burn in large patches at a higher frequency (up to 19 times in 24 years) [see Asner & Alencar (2010) for a review]. However, in the last decade (2000–2010), large forest fires were observed even in non-ENSO years (Alencar *et al*., 2011; Morton *et al*., 2013). The carbon emissions due to fires in Amazonia during 2010 and 2011, an extremely dry and wet year, respectively, were estimated as 0.51 ± 0.12 PgC yr^{-1} in 2010 and 0.25 ± 0.14 PgC yr^{-1} in 2011. In addition, forest degradation caused by forest fires produces relevant amounts of non-CO_2 greenhouse gases. Forest fires release CH_4, N_2O, ozone precursors, and aerosols (including black carbon), whereas forest regrowth after fire absorbs only CO_2. Globally, in 2010, non-CO_2emissions from deforestation and forest-degradation fires totaled 0.1 PgCO_2 eq. yr^{-1}, with forest management and peat land fires responsible for an additional 0.2 Pg CO_2 eq. yr^{-1}(Smith *et al*., 2014).

Despite the recent quantification of fire-affected areas by remote-sensing data, current methodologies are unable to disentangle different fire intensities and their on-the-ground impacts on forest structure and composition. In the Amazon region, understory fires burned more than 85 500 km^2 in the Amazon Basin south of the main course of the Amazon River between 1999 and 2010 (>80% in Brazil). Only 2.6% of forests that burned between 1999 and 2008 were deforested for agricultural use by 2010 (Morton *et al*., 2013). Cumulative fire-induced forest degradation needs to be quantified over longer time scales. Multiple fires in the same forest are rare but result in devastating effects on both forest biomass and biodiversity (Barlow & Peres, 2004; Alencar *et al*., 2011; Morton *et al*., 2013). Fire-induced tree mortality is highly variable (from 5% to 90%) (Balch *et al*., 2011; Brando *et al*., 2012) as are its effects on carbon stocks and subsequent forest recovery. Key aspects to be developed for efficient and effective monitoring programs of forest dynamics should include risk of fire (climate and topography, forest structure and available fuel material, and socioeconomic drivers), fire regime (seasonality, frequency, and human-dominated fire regimes), associated emissions (carbon, trace gases, aerosols, and committed vs. net emissions), and ecosystem impacts (burned area and severity, mortality, post-fire succession, and recovery). Table 2presents a compilation of different remote-sensing products and some field studies.

Table 2. Components of a fire monitoring system associated to current capabilities and future needs of research and development

	Current capabilities	**Gaps/future needs**
Forecast	NASA/UCI (SST) INPE – Fire Danger Forecast (South America)	Short-term forecast (1 week) data integration w/weather forecast -Economic forecast -Fragmentation, landscape-level risk for fire spread -Characterization of fire regime (expected frequency, seasonality, intensity, etc.)
Active Fires	INPE – Monitoring of vegetation fires	-Limited ~1 km late afternoon coverage -Small fires -Algorithms for understory fires
Burned Area	NASA (MODIS): MCD64A1, MCD45, Understory (250 m) INPE, DEGRAD, PanAmazonia	-Attribution (separate by land cover and process) -Agricultural fires, Pasture burning, deforestation process, connecting BA to legal/permitted fires, -Higher resolution mapping, -Routine mapping of understory fires, validation/omission
Emissions	GFED4 INPE-GMAI (Group Modeling of the Atmosphere and its Interfaces) (South	*Spatiotemporal variability in combustion completeness, mortality; *trace gas emissions ratios and their diurnal/seasonal variability),

	Current capabilities	Gaps/future needs
	America) NASA-QFED	*fire duration (e.g., smoldering), *fire return interval (fuel loads), *validation (MOPITT, OCO-2, NO2, airborne, *in situ*, and tower), *resolution, *missing fire types
Post-fire recovery and impacts	-Tanguro Fire Experiment-IPAM (Brazil) -INPE/Embrapa (Amazonian states, Brazil) -IBAMA, PPCerrado -LiDAR-Embrapa -Cerrado Fire Experiment-UNB, USP (Brazil) -RR – Embrapa -IPEA/IPAM (Socioeconomic, health) -Global Canopy Program (2005, Socioeconomic/health)	Chronosequence of fire ages, intensities; postfire mortality, biodiversity (phylogenetic and functional diversity, too) Socioeconomic impacts (public health, transportation, etc.) Ecological impacts

It is also important to consider that synergisms among simultaneous disturbance vectors dramatically increase rates of forest degradation. The combined effects of drought and understory fires can lead to abrupt and fundamental changes in vegetation structure and dynamics. In particular, droughts can trigger fire-induced tree-mortality events that are large enough to substantially reduce forest carbon stocks (by killing trees and combusting woody debris) and accumulation, increase forest flammability (by increasing air dryness), and facilitate forest invasion by flammable grasses (by increasing light availability in the understory). Together, the modifications in forest structure and dynamics resulting from drought–fire interactions can create positive feedbacks between fire and grass invasion that lead to further degradation. For example, Silvério *et al*. (2013) showed that grass invasion following fire-induced tree-mortality events can increase the occurrence of high-intensity fires, as grasses produce more fine fuel than forests. These hot fires further increase tree mortality, the likelihood of grass invasion, and the potential for subsequent high-intensity fires, even in the absence of droughts. Forest fragmentation interacts with fire by creating flammable environments near forest edges that dry during prolonged dry seasons, increasing the fuel load and fire probability (Cochrane, 2001; Brando *et al*., 2014).

Interactions between degradation drivers were also demonstrated in Eastern Amazonia (Berenguer *et al*., 2014). In that study, forests submitted to both selective logging and understory fires became structurally more similar to secondary forests and stored, on average, 40% less aboveground carbon than undisturbed forests. The understanding of the impacts of selective logging as a degradation factor is still very limited (Sist *et al*., 2014). Although some studies point to a high retention of the biomass and biodiversity after logging (Putz *et al*., 2012), they mainly encompass planned timber harvesting rather than the widespread unsustainable logging activities witnessed in the tropics. Addressing this knowledge gap is important, especially considering the magnitude of the disturbances caused by unplanned logging operations (Asner *et al*., 2005a,b). Furthermore, almost half of primary tropical forests (+400 million ha) are considered for timber production by national forest services (Blaser *et al*., 2011).

In terms of natural disturbances, windstorms are another important ecological stressor that has been shown to drive forest degradation, particularly when these events are associated with forest fragmentation and fire disturbances. Although wind-related disturbances differ widely in terms of magnitude and intensity across the Amazon (Espírito-Santo *et al*., 2014), they may drive substantial losses in forest biomass (Negrón-Juárez *et al*., 2010; Espírito-Santo *et al*., 2014) and fragmented landscapes (Benchimol & Peres, 2015). These losses could be higher in previously burned areas, given that the modifications in forest structure caused by fires increase the exposure of individuals to wind-related damages. Although it is challenging and requires integration of different methods, quantifying the individual and combined effects of different drivers of forest degradation is key to obtaining accurate estimates of their impacts on carbon stocks.

Monitoring carbon and biodiversity – need for a unified strategy

Unifying carbon and biodiversity monitoring is important for two key reasons. First, although biodiversity within (and often across) biomes is not necessarily correlated with carbon stocks (Strassburg *et al*., 2010), there is growing evidence of a tighter link at local scales, where higher carbon stocks are often associated with forests that contain more endemic species or species of conservation concern (Lima *et al*., 2013; Gilroy *et al*., 2014). In this case, monitoring will be important to identify the extent to which carbon conservation is delivering the expected biodiversity cobenefits and to assess whether the link may be modulated by anthropogenic impacts such as hunting pressure (Peres & Palacios, 2007) or landscape-level area and isolation effects, such as time lags to species extirpation or colonization (Gibson *et al*., 2013). Second, concerns about integrating biodiversity and carbon are justified as there is growing evidence that forest species composition and functional diversity are important for supporting forest carbon sequestration (Bunker *et al*., 2005; Conti & Díaz, 2013) and key ecosystem functions, such as secondary seed dispersal (Griffiths *et al*., 2015). In this case, monitoring may be required to evaluate the abundance of functionally relevant sets of species such as seed dispersing mammals and birds, or to examine how important ecosystem processes are mediated by biodiversity.

The many linkages between carbon and biodiversity mean that biodiversity monitoring should be considered in every stage of the REDD+ process, from planning and design to implementation and assessment (Gardner *et al*., 2012). This could be achieved through a common framework based on a tiered approach partially analogous to the IPCC guidance on tiered-emissions reporting, where the distribution of threats to biodiversity and the corresponding responses could be monitored simultaneously with carbon. As well as answering important questions about carbon and biodiversity cobenefits, such long-term monitoring efforts are also likely to be scientifically rewarding: some of the most important insights regarding the ecological consequences of human actions have come from long-term assessments of human impacts in tropical forests (e.g., Laurance *et al*., 2011; Gibson *et al*., 2013).

Nevertheless, designing effective biodiversity monitoring in degraded environments is challenging. Many countries have developed standardized biodiversity monitoring schemes to examine ecological change over time. These include the National Ecological Observatory Network in the USA and the breeding bird survey in the UK. Within the tropics, existing biodiversity monitoring initiatives focus mainly on undisturbed sites, for example ‘Tropical Ecology Assessment and Monitoring Network’, ‘Center for Tropical Forest Science’, and ‘Program for Biodiversity Research Studies’. However, new initiatives are currently being established to monitor biodiversity in degraded primary forests and secondary forests, such as ECOFOR in Brazil and Partners in Costa Rica. These initiatives indicate that some taxa (e.g., frogs, birds, large vertebrates, trees, ferns, ants, dung beetles, stream fish, and crustaceans) are particularly suitable for monitoring over long time scales.

Within degraded forests, there is a tension between adopting standardized approaches, thereby ensuring comparability across sites and adopting methodological protocols that are best able to respond to the most pertinent questions in the particular study landscape. RAPELD, a sampling strategy combining rapid assessments and long-term ecological research, is the dominant long-term monitoring methodology in Brazil and has the advantage of providing a modular system that records many variables, including those related to carbon dynamics (Magnusson *et al*., 2013). There are similar opportunities to build on existing initiatives, such as the NFIs (e.g., Brazil, Peru, Colombia, and Mexico), and the PPBio in Brazil, Nepal, and Australia. Alternative approaches involve organizing monitoring activities around catchments, which is sensible where concerns about forest carbon are linked to hydrological services or freshwater biodiversity. This was the approach taken by the Sustainable Amazon Network that assessed responses of six taxonomical groups to gradients of forest disturbance across thirty-six 50-km^2 catchments in eastern Amazon (Gardner *et al*., 2013). This network has revealed how forest degradation by fires, selective logging, and fragmentation can profoundly impact both biodiversity and carbon (e.g., Moura *et al*., 2013; Berenguer *et al*., 2014), with cascading consequences for the integrity of aquatic systems (Leal, 2015). Whatever the chosen sampling design, it is important that it captures the main anthropogenic stressors in the system of interest, which are likely to vary on a site-by-site basis. Furthermore, monitoring efforts will need to be fully integrated with local institutions to ensure longevity and adequate taxonomic support and will often be reliant on strong and long-lasting relationships with local landholders. None of these activities is trivial and will often require local training, capacity building as well as knowledge exchange, and dissemination activities.

Biodiversity monitoring may be facilitated using semi-automated approaches such as acoustic monitoring and camera trapping, which have several advantages in terms of cost-effectiveness over time and links to data analysis (O'Brien *et al*., 2010; Aide *et al*., 2013a,b). Waldon *et al*. (2011) proposed a standardized protocol for monitoring biodiversity for REDD+ using camera trapping for large vertebrates and bioacoustics for bats. Camera traps have several advantages:

they are cost-effective over time; they can operate day and night (infrared), all year round, in nearly any landscape; batteries last for months; photos are automatically date/time stamped; and images can be linked to data analysis tools (Waldon *et al*., 2011). They may be particularly useful for REDD+ biodiversity monitoring programs, especially if capture rates of target species are high, costs are relatively low, target species respond consistently and rapidly to habitat condition changes, and suitable flagship conservation species exist that can be used to help raise the profile of a project. Bioacoustic monitoring of target species is another powerful tool for estimating faunal biodiversity. Birds and bats have great potential as bioindicators for several reasons: they have a broad pantropical distribution and comprise many species, including threatened ones; they show taxonomic stability; they provide important ecosystem services and respond predictably to changes in habitat conditions; and they can reflect changes in arthropod prey communities and/or availability of fruit (Jones *et al*., 2009; Waldon *et al*., 2011; Harrison *et al*., 2012). Automated digital recording systems can monitor a wide range of animal populations, and Web applications facilitate data management and tools for creating species-specific algorithms to automate the identification of birds, amphibians, and insects (Aide *et al*., 2013a,b). Such studies of soundscapes can provide useful information on biotic, environmental, and human activities change through time (Pijanowski *et al*., 2011).

These technological solutions are not without their problems. The operational requirements and costs of running camera trapping or bioacoustics surveys programs may limit their utility by REDD+ project stakeholders (Harrison *et al*., 2012), and it can be difficult to deploy expensive equipment such as camera traps in human-modified landscapes where traps can be stolen or vandalized by hunters and other forest users. Bioacoustic monitoring is also limited at present: ultrasonic acoustic detectors cannot detect nonecholocating bats, and many forest-dependent tropical species use relatively quiet and short-duration echolocation pulses, which are difficult to detect. Location-specific and species-specific solutions are required to overcome such constraints, such as additional monitoring of calls in the nonultrasonic, physical trapping, and camera traps (Harrison *et al*., 2012). Finally, bioacoustics and related field-based biodiversity monitoring approaches retain a spatial mismatch with most habitat remote-sensing methods (Boelman *et al*., 2007).

While many modern methods can be very effective, there are many uncertainties in biodiversity monitoring that have little to do with technological or statistical aspects (Magnusson, 2014). Efforts have been made to provide efficient methods suitable for community-based (Angelsen *et al*., 2012) and participatory forest monitoring of carbon and biodiversity for REDD+ (Casarim *et al*., 2013), including smartphone applications for community-based biomonitoring (Moran *et al*., 2014). Yet, all fieldwork-based efforts will be constrained by the challenges of covering huge spatial areas and the limited expertise in species identification. Remote-sensing techniques have been experiencing some advance in recent years and may provide solutions to some of these issues. In particular, airborne spectranomics approaches (Asner & Martin, 2009) based on the leaf chemistry, physics, and the taxonomy of canopy trees that are opening new paths for tropical forests monitoring, including plant diversity. Recent technologies can map chemical and structural traits of plant canopies and are promising for monitoring vegetation biodiversity, species range, and functional traits (Goetz *et al*., 1985; Schimel *et al*., 2013). In addition, a more coherent collection of field trait data together with proximal and remote-sensing observations will allow us to understand the interaction between plant structural, physiological, biochemical, phenological, and spectral properties and then to develop robust scaling schemes to support airborne and satellite-based methods of trait estimation (Homolová *et al*., 2013). Technologies such as imaging spectroscopy and LiDAR can innovate airborne, tropical-forest diversity mapping. Recently, Asner *et al*. (2015), using visible-to shortwave infrared imaging spectroscopy with LiDAR, assessed the foliar traits of Amazonian and Andean tropical forest canopies. This new airborne approach could address limitations and sampling biases associated with field-based studies of forest functional traits in complex tropical canopies.

While indirect approaches using remote sensing offer valuable information (derived from biophysical characteristics and environmental parameters) about diversity patterns, other approaches are addressing direct remote sensing of certain aspects of biodiversity (Turner *et al*., 2003; Pettorelli *et al*., 2005). Protocols that can integrate remote sensing and on-the-ground biodiversity assessments can be effective to evaluate both structural and functional degradation. Cryptic mechanisms of forest degradation, such as overhunting, could reduce the strength and diversity of ecological interactions before more detectable patterns of forest degradation occur (Peres *et al*., 2006). Future development should consider how to integrate requirements and protocols for carbon accounting, sociocultural/socioeconomic impacts, and biodiversity outcomes.

A network of sites distributed across the tropics would help to answer questions about trends in terrestrial tropical biodiversity and calibration/validation of remote-sensing tools if each site captured landscape variation using a spatially explicit system, such as RAPELD (Costa & Magnusson, 2010). These sites could be used for a variety of purposes, but would need to have a minimum set of essential biodiversity variables (EBVs) measured at each site (Pereira *et al*., 2013). The cost of setting up such sites is moderate depending on the practicalities of logistical access, how frequently surveys are repeated, and which vertebrate, invertebrate, and plant taxonomic groups are sampled (e.g., Gardner *et al*., 2008). For example, the installation of a 5-km^2 RAPELD sampling module in Brazil by a team of five experienced technicians is currently about US$10 000, but varies depending on transport costs to the site. This compares favorably with one-off or repeated standardized line-transect surveys of medium- to large-bodied vertebrates, including understory mist-netting of birds, in many remote forest sites of lowland Amazonia, each of which cost an average of US$6000 (C.A. Peres, unpublished data). Monitoring of a suite of EBVs could be performed for less than US$20 000 in general operating costs per site per year because most EBVs can be efficiently measured at intervals of 2–5 years. However, as with any *in situ* system, the highest costs are associated with maintenance of scientific presence and training. Inclusion of local researchers and students not only reduces costs, but is typically critical to the success of the sampling program. Many tropical countries resent recent experiences with colonial domination and intellectual imperialism and are unlikely to allow foreign researchers to access whether there are no perceived capacity-building benefits to the country beyond those of possible global governance of environmental changes. Based on current costs in Brazil, the cost of maintaining a field team capable of installing infrastructure and providing capacity building for five sites per year is about US$1 500 000. Costs could possibly be reduced by the use of previously installed capacity in countries such as Australia and Nepal. There is also much capacity already installed for data management and analysis in networks such as Data Observational Network for Earth (DataOne), Amazon Forest Inventory Network (RAINFOR), and Amazon Tree Diversity Network. These preliminary cost estimates indicate that it is feasible for the world community to meet most of its obligations relating to biodiversity under REDD+, maximize the use of new remote-sensing tools, and undertake the most ambitious capacity-building program in biodiversity that has ever been undertaken.

Integrating monitoring and ecosystem modeling: move toward more process-oriented approaches

A better understanding of forest dynamics requires the transition from the concept of carbon stock change toward a more process-oriented description of forest dynamics (recruitment, mortality, growth dynamics, and species composition), and how these processes are modified by direct anthropogenic disturbances (e.g., fire, logging, edge effects, and land conversion) and extreme climatic events (e.g., severe droughts, floods, and storms). Accounting for environmental impacts on forests over long time periods (at least several years) requires the consideration of not only external environmental changes (e.g., climate and deposition) but also changes in the vegetation itself that affect microclimatic conditions and carbon allocation

(Grote *et al*., 2011). Allocation in trees is often modeled under the assumption that the ratios between leaves, stem, and roots remain constant, within certain boundaries depending on species, and that tree height is the main parameter describing the effects of site-specific growing conditions. Even though allometric functions describe total biomass as a function of height and diameter over a surprisingly large range of conditions (Wirth *et al*., 2004), these functions do not predict tree age, which is important for estimating carbon turnover (Schulze, 2014), or wood density, critical for carbon content.

Forest inventories and eddy covariance measurements contribute to sustainability assessments as well as carbon accounting. A differentiation between ecosystem compartments of carbon, such as soil and vegetation, or above- and belowground storages, nevertheless requires further empirical estimates or model simulations. However, models to estimate carbon balances often do not account for carbon export during logging or the direct and indirect impacts of forest management (Grote *et al*., 2011). In addition, observational or experimental studies of ecosystems focus on local scales of less than a hectare for measurements of vegetation and <1 km^2 when using flux towers. The extrapolation to landscapes remains uncertain, because we do not know the spatial variation in environmental conditions and how this might affect ecosystem processes. Thus, there is a scaling problem when moving from plot-scale studies to landscapes. Scaling could be facilitated by the use of remotely derived variables, such as leaf area index from NDVI data (Schulze, 2014).

The integration of ecosystem models on a spatially explicit basis with monitoring systems represents a promising pathway to move toward a more process-oriented description of forest dynamics. Figure 4 represents the integration of field and remotely sensed data and ecosystem modeling to understand forest degradation and recovery. In many cases, the modeling framework exists, but appropriate parameterizations and data assimilation are still needed as more explicit representation of soil/plant water relations (from 'big leaf' to tree model) and stand dynamics (e.g., demography models) to allow the treatment of recruitment/mortality, and forest structure. These models will be more diagnostic and not prognostic, but could be appropriate for understanding C-balance change in the kind of operational mode described here (e.g., spatially explicit, with ecosystem models improving estimates of fluxes).

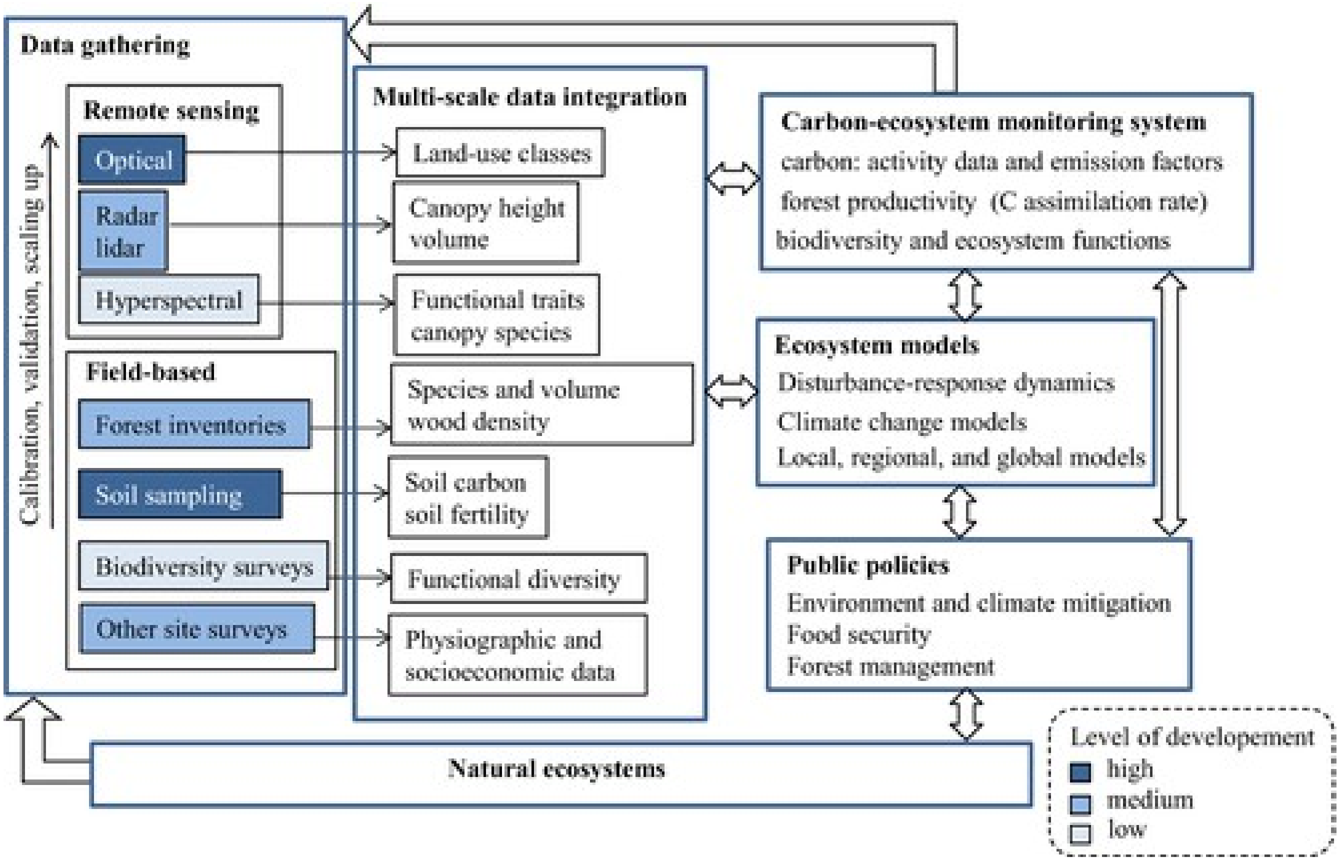

Figure 4

Open in figure viewerPowerPoint

Spatially based, multiscale integrative framework for monitoring and modeling carbon stocks and biodiversity.

An analysis of the approaches currently underway with focus on carbon stocks and fluxes, biodiversity, and drivers of forest degradation indicates that the major limitations for all model types are the lack of data for parameterization and the cost to run models at high spatial resolution. This brings the question about the appropriate spatial resolution. Current book-keeping approaches provide land-use transition and estimates of C emission/regeneration at spatial scales of 5 km resolution (e.g., INPE-EM, Aguiar *et al*., 2012). Although some book-keeping models include socioeconomic information, such as repeated cutting of secondary vegetation, they do not consider climate interaction or soil fertility. Fire models are also spatially explicit but provide emissions only. The application of ecological models at this scale would add information on nutrient limitation, decomposition rates, and growth rates, among other variables for the estimation of spatial variation in NPP and regrowth dynamics. Nevertheless, data assimilation capability is not currently implemented in ecosystem models.

Quantitative models are frequently employed to address the complexities associated with disturbance processes. Seidl *et al*. (2011) reviewed the variety of approaches to modeling natural disturbances in forest ecosystems (from single events to integrated disturbance regimes) in relation to disturbance agents and mechanisms. The number of disturbance-modeling approaches emerging over the last 15 years has increased strongly but statistical concepts for descriptive modeling are still largely prevalent over mechanistic concepts for explanatory and predictive applications that are crucial for understanding and coping with change in forest ecosystems. The authors also identified the current challenges for disturbance modeling in forest ecosystems as the following: (1) to overcome remaining limits in process understanding, (2) to further a mechanistic foundation in disturbance modeling, (3) to integrate multiple disturbance processes in dynamic ecosystem models for decision support in forest management, and (4) to bring together scaling capabilities across several levels of organization with a representation of system complexity that captures the emergent behavior of disturbance regimes.

Modification of current models to first address the largest unknowns should be prioritized, recognizing that different model development/information streams will be required for a synthesis framework. Advances in the current state of knowledge involve complementary efforts for field collection to supply needed parameters, the use of already installed permanent plots to support functional trait-based approaches, as well as the use of available data bases (e.g., converting taxonomic information into functional groups, trait data bases), and the analysis of what traits could be extracted from new data streams (e.g., LiDAR, hyperspectral data). Soil data from forest inventories could be used to improve the analysis of spatial and temporal variation in soil nutrients. Significant efforts need to be put toward model development/validation, especially toward exploring how to better apply data assimilation.

A synthesis of data from areas identified as being most dynamic in terms of biomass change is also relevant for understanding the spatial configuration of biomass loss. Biomass data will ultimately be provided by remote sensing (e.g., ESA Biomass mission will provide data after 2020, LiDAR in 2019), but the models have to contribute to explanations of why the biomass is distributed the way it is and also how biomass relates to function, resilience to disturbance, and biodiversity metrics. Rates of biomass accumulation following disturbance and how those are influenced by climatic and soil parameters as well as the pattern of landscape disturbance (e.g., distance to seed source) affect how much C is released (net emissions).

Research priorities for forest monitoring systems

The determination of ecosystem carbon balances is a major issue in environmental research. Research on disturbances inducing forest degradation and subsequent recovery is necessary to understand the causal factors related to C-stock changes and associated emissions. Although the assessment of deforestation due to clear-cutting is well developed, monitoring of degradation, regeneration of forests and their environmental consequences also requires greater efforts. Current monitoring methods (remote-sensing and field data) have shortcomings in the assessment of temporal changes of forest inventories associated with degradation, as well as forest regeneration. The limitations on the quantification of degradation and forest recovery remain major constraints for the verification of results required by the REDD+ mechanism. Additional research efforts could help to augment long-term monitoring efforts with a focus on important aspects of the carbon loss pathways (e.g., combustion, decomposition, and soil carbon dynamics) and on direct manipulation experiments or space-for-time studies.

It is crucial to quantify and reduce uncertainties in relation to fire effects and their impacts. Future research should move to improve validation (active fires, burned area, emissions ratios, fire effects – short and long term), downscaling (higher resolution mapping, attribution to specific land-cover types, and processes of degradation/deforestation/management), and data integration (scales, models, networks linking ground data, national monitoring efforts, and also international networks of fire research).

Forest monitoring captures human impacts and other biotic and abiotic influences on forests. Detailed data are collected at stand level, and often integrated in larger forest-observation networks, which feeds into forest-ecosystem models. However, forests exist in a constantly changing societal context, and the direct or indirect impact of human activity has become a crucial driver of all types of ecosystems (Daume *et al*., 2014). History of disturbance/regrowth/deforestation depends on social, economic and climate drivers. Socioeconomic drivers are also important to determine the future trajectories of land use and, thus, should be coupled to dynamic ecosystem models. Socioeconomic drivers (e.g., the advance of the agricultural frontier, the installation of infrastructure projects or population movements) (Perz & Skoleb, 2003; Perz *et al*., 2011; Walker *et al*., 2013) also require research and perhaps can be modeled more explicitly in concert with ecological models. Emissions are often more dependent on socioeconomic causes than natural ones. To explicitly refine estimations, these factors need to be spatialized.

Monitoring must be consistent and continuous. There are new perspectives both with regard to the availability of data, and processing approaches and capacity. In particular, there is the expectation about the synergy between the Landsat 8 – began normal operations on May 2013, and provides seasonal coverage of the global landmass at a spatial resolution of 30 m (visible, NIR, SWIR), 100 m (thermal), and 15 m (panchromatic) (Roy *et al*., 2014) – and the two new Sentinel 2 satellites (Sentinel 2a was successfully launched on June 23, 2015, and Sentinel 2b should be released in April, 2016) (Drusch *et al*., 2012). Working as a constellation, they could provide data for the same area over five to ten days (the sensors of these three satellites were previously precalibrated). This means that the temporal resolution of MODIS (via time series) will be replicated to a spatial resolution (at least) 64 times higher. Data of this nature will be extremely useful to map processes related to plant traits and cryptic degradation. As for the processing capacity, platforms using cloud computing (e.g., Google Earth Engine) can process Landsat 8 images rapidly and could improve spatial resolutions of models and interactions involving a much larger number of variables. While potential contributions from new satellite missions are recognizable, we also must be realistic about how some of these future efforts will be translated in operational forest monitoring systems (e.g., a 1-year GEDI LiDAR mission in 2018–2020). However, the combination of field inventories and ecosystem modeling with new remote-sensing tools can open new opportunities for faster progress of operational systems. Complementary efforts of field collection are needed to provide more precise parameters and contribute to the explanation of how the growth performance is influenced by climate and soil aspects. The ecological modeling should add information on processes that influence the responses of forests to disturbances, such as nutrient limitation, decomposition rates, and growth rates.

A way forward to an integrated framework

While assessment of deforestation is well developed, forest degradation is neither well assessed nor validated adequately. Forest degradation (unlike deforestation) is not binary, but rather a continuum. Monitoring systems for forest degradation, whether based on *in situ*or remotely sensed data (or more likely a combination) depend upon operational definitions limited by the sensitivity of the measurement approaches employed. Current degradation estimates differ due to the interaction between different processes, such as logging and fire, temporal mismatch, scale of analysis, and threshold effects. Successful monitoring of degradation will have to be linked to viable quantitative-measurement approaches. A summary of the main points on how to move forward with the scientific agenda and implementation of improved monitoring systems of forest dynamic is presented in Table 3. The recommendations were divided into the following topics: (1) Mobilization of stakeholders and scientific community to include an integrated framework in the political agenda, (2) Harmonization of national monitoring programs and existing initiatives, (3) Integration and optimization of ecosystem models to improve process-level understanding carbon and forest dynamics, (4) Development of a permanent plot field network to calibrate, validate, and combine multiscale sampling and monitoring methods, (5) Improvement of the understanding of forest drivers and postdisturbance trajectories, (6) Inclusion of parameters related to forest fire drivers and impacts in a monitoring program, and (7) Evaluation of biodiversity and carbon values under a unified strategy.

Table 3. Summary of research priorities and practical recommendations to help achieve an integrated framework

Mobilization of stakeholders and scientific community to include an integrated framework in the political agenda

1. Define objective-oriented research efforts (problem and goals) in an integrated framework
2. Survey institutions, researchers, and ongoing research projects to capitalize on proven monitoring strategies and accompany testing of new, state-of-the-art methods
3. Solicit input through workshops of experts and stakeholders to hone the design of multi-purpose monitoring programs, with careful attention to implementation networks at national, regional, and local scales
4. Secure funding for long-term monitoring efforts, based on key products and outcomes of the integrated framework
5. Develop specific proposals and defining possible products and outcomes
6. Establish a program within the network that can be integrated with other objectives and goals
7. Establish a national-level, long-term program involving different government levels, research institutions and international cooperation
8. Include explicit articulation of how the monitoring programs will inform environmental policies
9. Specify thresholds that should guide the implementation of strategic interventions from monitoring programs (periodic reviews of protocols and achievements)
10. Foster local capacity and integrate monitoring efforts with local institutions and communities to inform and encourage communities and social groups to participate in decision-making processes related to the environment

Harmonization of national monitoring programs and existing initiatives

1. Make a comprehensive survey of different ongoing initiatives
2. Improve technical and scientific exchange to gather and process information for integrative approaches
3. Promote the interaction of developers and end users of monitoring programs to establish clear guidelines for the development of monitoring systems and their products
4. Promote free data access by data-use policy

Integration and optimization of ecosystem models to improve process-level understanding carbon and forest dynamics

1. Identify primary modeling research needs: which models are needed and which data are required to parameterize, calibrate, and

validate models

2. Promote combined efforts for model development/validation, especially toward exploring how to best apply data assimilation
3. Integrate ecosystem models on a spatially explicit basis with monitoring systems
4. Use taxonomic data from installed permanent plots to support functional trait-based approaches
5. Determine traits that could be extracted from new data streams (e.g., LiDAR, hyperspectral data)

Development of a permanent plot field network to calibrate, validate, and combine multiscale sampling and monitoring methods

1. Survey of existing permanent plot networks and important information to build upon existing initiatives, such as spatial location of plots, network objectives, variables, sampling methods, frequency, institutions, and publications
2. Use remote-sensing and ancillary data to help select strategic areas and stratify areas of interest, such as degraded forests, according to research and modeling needs, knowledge gaps, and regional differences
3. Select areas and plots for multiple purpose field surveys (forest structure, soil, social and economic data, landscape, etc.) and for validation of airborne and satellite remote sensing
4. Integrate airborne and satellite campaigns on selected plots for calibration and validation

Improvement of the understanding of forest drivers and postdisturbance trajectories

1. Identification, quantification, and monitoring of forests undergoing deforestation, degradation, and recovery
2. Develop a spatially explicit map of secondary forest and their turnover, plant and faunal diversity, and nutrient availability
3. Evaluate appropriate time intervals for temporal reassessments needed to examine recovery and resilience of forests
4. Make wall-to-wall assessments and temporal reassessments, using appropriate time intervals to study forest recovery and resilience
5. Include socioeconomic drivers of land use trajectories to dynamic ecosystem models
6. Determine how climatic and soil parameters and landscape disturbance affect postdisturbance dynamics
7. Quantify combined effects of different drivers of forest degradation, such as effects of drought and understory fires on forest degradation and dynamics
8. Determine the impacts of unplanned logging operations as a degradation vector

Inclusion of parameters related to forest fire drivers and impacts in a monitoring program

1. Improve validation (active fires, burned area, emissions ratios, fire effects – short and long term)
2. Include risk of fire parameters (climate and topography, forest structure and available fuel material, and socioeconomic drivers) and fire regimes (seasonality, frequency, and human-dominated fire regimes)

3. Determine associated emissions: carbon, trace gases, aerosols, and committed vs. net emissions
4. Assess ecosystem impacts: burned area and severity, mortality, postfire succession, and recovery

Evaluation of biodiversity and carbon values under a unified strategy

1. Determine opportunities and tradeoffs for multitaxa field surveys
2. Establish a common framework based on a tiered approach, where the distribution of threats to biodiversity and the correspondent responses could be monitored simultaneously to carbon
3. Integrate carbon accounting, sociocultural/socioeconomic impacts, and biodiversity outcomes

Building an integrated monitoring framework requires adequate and long-term financing. Strong efforts are needed to include it in the political agenda and stimulate the scientific collaboration community and harmonize existing monitoring programmes. The development of such framework can be separated into four main strategies: (1) integration and optimization of ecosystem models to improve process-level understanding; (2) development of a permanent plot field network to calibrate, validate, and combine multiscale sampling and monitoring methods; (3) optimizing scaling up methods to extrapolate estimates for larger scales; and (4) defining how a monitoring system will assist public policy actions.

Efficient monitoring systems must have the following characteristics: representative spatial coverage, standard sampling, long term, consistency, precision, calibration, openness/transparency, and good documentation. Many monitoring systems are designed for specific purposes (such as reporting for specific variables) and, thus, include a limited number of variables or parameters. Harmonization will require changes to monitoring programs and inventory systems, which might lead to resistance, due to lack of funding or institutional barriers (Magnusson *et al*., 2013). At the country level, harmonizing monitoring programs into a national system, instead of independent initiatives, would be helpful to minimize such barriers. It is important to open up pathways to discuss future synergistic efforts (e.g., biodiversity and other variables in field surveys, integrating field-based systems to remote-sensing efforts, opportunities, and tradeoffs for multitaxa field surveys).

Important recommendations to foster new monitoring strategies to address to new environmental and societal needs are a comprehensive survey of different ongoing initiatives (e.g., NFIs), improvement of technical and scientific exchange to gather the information available and definition of how to use them in the development of integrative approaches. In this context, developers and end users need to interact to establish clear guidelines for the development of reliable products. Validation and calibration of monitoring systems are an essential part and should include an appropriate and robust design (number of points, areas – including those with existing studies, cover all biomes) as well as the verification of outputs of each model ensuring the quality and transparency of results.

The design of monitoring programs must also consider that in addition to capturing valuable information, it is central to inform communities and social groups and so encourage their qualified participation in decision-making processes relating to the environment. Attributes to ensure the effectiveness of monitoring programs include explicit articulation of how the monitoring will inform environmental policies and programs, clear specification of thresholds that affect the implementation of strategic interventions from monitoring programs, and a precise quantification of the ability to achieve early detection of changes being monitored.

Acknowledgements

This document is based on the discussions held during the *Workshop on Monitoring Forest Dynamics: carbon stocks, greenhouse gas fluxes, and biodiversity,* in Brasilia, Brazil (September 2–4, 2014) financed by Climate Land Use Alliance. Susan Trumbore and Douglas Morton acknowledge the financial support from the *Science Without Borders Program* (CNPq). Mercedes Bustamante and Iris Roitman acknowledge the financial support of the Rede Clima of Brazilian Ministry of Science, Technology and Innovation. J.B. and E.B. were supported by a grant from the NERC (NE/K016431/1). The authors are grateful to Toby Gardner for valuable comments on previous version of this article.