Approaches to monitoring changes in carbon stocks for REDD+

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Reducing emissions from deforestation and forest degradation plus improving forest-management (REDD+) is a mechanism to facilitate tropical countries' participation in climate change mitigation. In this review we focus on the current state of monitoring systems to support implementing REDD+. The main elements of current monitoring systems – Landsat satellites and traditional forest inventories – will continue to be the backbone of many forest-monitoring systems around the world, but new remote-sensing and analytical approaches are addressing monitoring problems specific to the tropics and implementing REDD+. There is increasing recognition of the utility of combining remote sensing with field data using models that integrate information from many sources, which will continue to evolve as new sensors are deployed and as the availability of field data increases.

Carbon emissions from deforestation and forest degradation in tropical regions are estimated to be 2.9 PgC per year, equivalent to 38% of the carbon emissions from fossil fuels during the years 1990–2007 [1]. On the other hand, tropical forest regrowth amounts to a carbon sink of 1.6 PgC per year, which offsets a significant proportion of emissions, resulting in a net carbon balance in tropical forests of -1.3 PgC per year. REDD+ is a mechanism proposed by the UN to facilitate tropical countries' participation in climate change mitigation. According to the IPCC [2], reducing deforestation is the forestry mitigation option with the largest and most immediate effect on atmospheric CO_2 concentration.

First proposed at a COP to the UNFCCC in 2005, REDD (without the +) generated a great deal of interest among countries with high rates of deforestation and forest degradation, because under the proposed program, they could receive payments from other countries or entities that wished to offset their fossil fuel emissions [201]. Initially, the nature of REDD did not allow for participation by countries that were already highly deforested or had low rates of deforestation; hence, the '+' was added as a way to encourage participation by countries where improvements in forest management, conservation and enhancement of forest carbon stocks could be included in the REDD mechanism.

In this review we focus on the current state of monitoring systems to support implementing REDD+ in tropical countries. Monitoring requirements for the three main activities – hereafter referred to as deforestation, degradation and improving forest management – confer unique challenges, as well as the need to be integrated into a holistic approach that is also consistent with other forest monitoring requirements. For example, in addition to implementing programmatic activities, such as REDD+ on specific areas, tropical countries are also required to periodically report national GHG emissions and sinks [202].

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Key term

Allometric equations: Establish a quantitative relationship between characteristic dimensions of trees such as diameter of the bole or total tree height, and another tree property such as volume or biomass, which is much more difficult to measure directly. This relationship is typically based on detailed measurement of the desired tree property on a small number of trees representing a population of interest, and then extrapolated to a much larger sample of trees based on the allometric relationship to the simpler measurements, which can be widely deployed.

Reporting and monitoring guidelines are available from different sources, including the IPCC and the UN, among many others [3]. However, in application, monitoring programs to support REDD+ are still evolving as countries grapple with implementing the appropriate methods in varying national circumstances such as existence of national or regional inventory and monitoring systems, stability of institutions to conduct the monitoring, and availability of expertise to perform the required planning, data collection and analyses.

The broad theme of this review is to provide guidance on emerging approaches to measurement, reporting and verification (MRV) in tropical countries, and how to deploy these approaches so that MRV systems can evolve to meet future needs. Elements of approaches included in this review are forest inventories, remote-sensing, intensive monitoring sites and models, which may be integrated for MRV purposes including estimation of uncertainty. Traditional forest inventories, often targeted to timber assessment and therefore not usually measuring all carbon pools, must be augmented with additional observations and data required specifically for REDD+, including information needed to build models to improve estimates of the different carbon pools. Improvements may be needed in remote sensing of land cover and land-cover change for detecting deforestation and degradation, and more intensive field observations are required to assess effects of these activities and natural disturbances on above- and below-ground biomass, dead organic matter and soil carbon pools. Models are fundamental to making useful estimates from available data and are also required to project baselines of anticipated future GHG emissions under scenarios of 'business-as-usual' rates of deforestation, degradation and improved forest management. Baselines are also compared with the actual emissions and removals, and form the basis for the accounting of credits or debits resulting from the implementation of REDD+ strategies. Improvements in estimation processes are needed to integrate multiple data sources and models and assess the uncertainty of complex estimation methods.

This review is based on recent work in selected tropical countries, as well as established forest inventory and monitoring systems in temperate and boreal countries. In many countries, MRV systems are being actively developed and tested following the general guidelines provided by the IPCC, the FAO and other international organizations. For example, the US 'SilvaCarbon' program provides technical advice and assistance from different agencies regarding the use of remote sensing and inventories, including currently active programs in Peru, Ecuador, Colombia, Gabon and Vietnam [203]. Mexico is among the few tropical countries that already have an established national forest inventory with repeated measurements to use as a strong foundation for MRV. Some countries such as Ecuador have recently completed a first national forest inventory, Colombia is developing a proposal for an MRV system and national forest inventory, while Peru has designed and is just beginning to implement its national forest inventory.

Monitoring & reporting requirements for REDD+

The UNFCCC national GHG inventory reports require estimates of GHG emissions and removals by economic sector, including 'land use, land-use change and forestry'. Estimation and reporting guidelines are provided by the IPCC Task Force on National Greenhouse Gas Emissions [204], and are documented in the '2003 Good Practice Guidance' and the '2006 IPCC Guidelines for National Greenhouse Gas Inventories' [4,5]. The technical guidance for the forest sector recognizes individual countries' national circumstances by providing flexibility in methodology, and a three-tiered approach:

- Tier 1: uses IPCC default values for carbon stocks in different ecoregions and country-specific activity data;
- Tier 2: uses country-specific data about forests and carbon stocks within detailed strata, and country-specific activity data;
- Tier 3: uses inventories with repeated direct measurements of changes in carbon stocks, or models parameterized with country-specific data, and country-specific activity data.

Moving from tier 1 to tier 3 increases the level of effort required and therefore the cost of the monitoring system, but improves the accuracy of estimates and utility of the information for assessing alternative mitigation approaches. Countries are encouraged to use the best possible methodology appropriate to their national circumstances and to improve estimates over time by moving from lower to higher tiers, and by identifying, quantifying and reducing uncertainties as far as practicable. In the context of the IPCC, reducing uncertainties in GHG inventories refers to the uncertainty of the reported estimates and all of their components, which may include uncertainty arising from the use of default volume to biomass-expansion factors, sampling, modeling and systematic errors, to name a few of the possible contributors to uncertainty. The IPCC does not predetermine a required level of precision; rather, countries are encouraged to use the uncertainty analyses to help improve the accuracy of inventories and guide decisions on methodological choices. The IPCC guidelines provide information about estimating uncertainty for the different estimation components of each tier [4,5].

With respect to REDD+, national GHG inventories provide an important large-scale benchmark that reflects the net effect of all factors, both anthropogenic and natural, that affect 'managed forests', as defined by each country. Estimates of the effects of activities falling under REDD+ should be consistent with the national-scale estimates for managed forests; however, REDD+ activities are likely to be targeted to specific projects or regions, and so national inventories that do not include intensified sampling in areas of change may not provide estimates of emissions reductions from activities such as deforestation, which affect only a small percentage of the forest area annually (annual average of 0.6% of forest area globally) [1].

National GHG inventories inform policymakers about the magnitude of emissions associated with deforestation and degradation, and thus the importance and urgency of investing in their avoidance. They also inform policymakers about opportunities to increase carbon stocks through improved forest management. Another important function of the national inventories is to provide country-specific standards for measurement, estimation, reporting and accounting within the established international guidelines. National standards then provide guidance for estimation at the smaller scales of individual projects, such as the definition of a forest and the different forest carbon pools, and elements of estimation methods such as biomass equations. National standards allow estimates at different scales to be consistent and additive.

Markets and GHG registries are often targeted to individual projects or legally defined entities such as companies, individual landowners, NGOs and communities. Each market or registry has its own reporting requirements that typically involve comparison of two scenarios – business-as-usual (without the project) and a second scenario representing the difference in carbon stocks or rates of change that result from the project. Ideally, these markets and registries conform to national and international guidelines so that any awarded or registered carbon credits are fungible. Usually, markets and registries specify an accuracy standard and require specific approaches for inventory and estimation, as well as clearly defining the acceptable activities, eligible entities and geographic scope (e.g., California's Climate Registry) [205].

Some policy approaches to REDD+ involve government regulations or incentives to land managers to change the practices applied to their land. For example, the Mexican government provides payments for ecosystem services (hydrological, but includes avoided deforestation), and these payments are based only on the area treated and maintained [6]. In the case of incentive programs, reporting may only require data about the area affected by allowable practices and assurance that the revised land management practices remain effective for a specified period of time, rather than a full accounting of the impacts on carbon stocks.

Elements of approaches

Estimating and mapping forest carbon and other typical inventory variables such as timber volume usually involves a combination of two or more methods: remote-sensing, field measurements, intensive sites and modeling. In this section we describe the basic elements that are being used for monitoring changes in carbon stocks, and some ways to integrate them into a reporting system. This is an active topic of research and several global initiatives are underway to improve integrated monitoring of forests from space and on the ground, such as the international program Global Observation of Forest and Land Cover Dynamics [206], and the Global Forest Observation Initiative [207].

▪ National forest inventories & traditional field methods

National forest inventories can be the foundation of a 'tier 3' approach to forest carbon monitoring, either as an initial inventory of stocks from which changes can be estimated based on knowledge of effects of different factors such as harvesting and natural disturbances, or as a direct estimate of stock change from repeated inventories. One of the main forest carbon pools, forest biomass, has traditionally been measured and monitored with forest inventory methods originally developed many decades ago for assessing timber supplies [7]. Forest inventories involve systematic or random selection of sampling locations in areas as large as countries; field measurements of tree parameters such as species, diameter and height; and **allometric equations** to estimate a variable of interest that is difficult to directly measure (e.g., timber volume or biomass) [8]. The inventory sampling approach provides unbiased estimates with known sampling uncertainty, although the uncertainty attributed to the use of allometric equations or models is infrequently estimated [9]. Monte Carlo estimation methods (discussed later in this Review) may be used to assess the overall uncertainty of a nation's GHG inventory [10]. National inventories are often targeted to assess the population of live and dead trees in a forest. Other ecosystem carbon pools may be estimated directly, with supplemental measurements added to the inventory or modeled using exogenous data [11]. Most of the global statistics on forest biomass and other forest

Key terms

Live trees: Live trees with a specified minimum diameter at breast height (diameter at breast height typically 2.5 cm), including carbon mass of coarse roots (typically greater than 0.2–0.5 cm), stems, branches and foliage.

Standing dead trees: Standing dead trees with diameter at breast height typically greater than 2.5 cm, including carbon mass of coarse roots, stems and branches.

Forest floor: Organic material on the floor of the forest, which includes fine woody debris up to 7.5 cm in diameter, tree litter, humus and fine roots in the organic forest floor layer above mineral soil.

Down dead wood: Woody material that includes logging residue and other coarse dead wood on the ground that is larger than 7.5 cm in diameter, and stumps and coarse roots of stumps.

Soil organic carbon: Belowground carbon without coarse roots, but including fine roots and all other organic carbon not included in other pools, to a depth of 1 m.

Understory vegetation: Live vegetation that includes the roots, stems, branches and foliage of tree seedlings (typically trees <2.5 cm diameter at breast height), shrubs and bushes.

Carbon in harvested wood: Includes products in use and in landfills. 'Products in use' include end-use products that have not been discarded or otherwise destroyed. Examples include residential and nonresidential construction, wooden containers and paper products. 'Products in landfills' include discarded wood and paper placed in landfills where most carbon is stored long term and only a small portion of the material is assumed to degrade, at a slow rate.

attributes reported by the FAO are based on national forest inventories [12], and in some cases, an image-sampling approach. From these comprehensive statistics it is possible to develop global estimates of biomass and other carbon pools for the last two decades based primarily on ground data, including forest inventories and other field sampling networks [1].

Allometric equations are used to estimate the biomass of individual trees from field measurements such as tree diameter and height. Typically, biomass equations are developed for a population of trees by harvesting and weighing a small sample of them across a range of diameter and/or height classes, and then estimating parameters of an equation relating biomass to these measured variables using regression techniques. Individual tree estimates may be expanded to the population of trees by knowing the probability of sampling each tree and the area to which the sample applies. Another approach is to derive an 'expansion factor' whereby biomass is estimated as a function of volume, which was previously estimated as a function of tree diameter and bole length. Variations on these standard methods are also possible [13,14]. In practice, especially for large regions, there is usually a scarcity of representative biomass or volume equations so that only a few equations are available, representing populations of trees that may be different from the population of interest [15]. This is particularly true in tropical regions where such work has been lacking, although the methods are well known [16]. Available local biomass equations may be aggregated to provide more generalized regional equations that may be used for large areas but are not necessarily appropriate for specific forest tracts that are not likely to be represented by a regional average value [8,17]. When local or species-specific biomass equations are not available, a typical situation in tropical forests, it is common to use a generalized biomass equation. Several general regression equations are available for estimating tropical forest biomass, and a recent study has shown that valid estimates of tree biomass for any species can be made using three independent variables: tree diameter, tree height and wood specific gravity [18]. Several different regression models may be used with these variables, and the models are likely to be less biased and have smaller residual standard errors if developed separately by forest type [18]. Countries may also wish to consult a new database of allometric equations available for use in estimating volume, biomass and carbon [208].

Estimating the change in biomass of **live trees** from forest inventories requires successive measurements of sample plots, typically the same sample plots measured at an interval of at least several years to allow accurate measurement of an average rate of change in tree diameter and height. Measurements should be made on individual marked survivor trees at both points in time, on trees that grow into the sample by crossing a minimum diameter threshold (ingrowth trees, measured at the second inventory), and on trees that died during the interval [19]. Corrections must be made for the timing of ingrowth or tree death to account for the actual increments that occurred over part of the time interval.

Other forest carbon pools – **standing dead trees**, **forest floor**, **down dead wood**, **soil organic carbon**, **understory vegetation**, and **carbon in harvested wood** – may be surveyed along with trees in a national inventory, or may be estimated with **empirical models** that relate these variables to standard inventory estimates of volume, biomass, forest composition, forest age and other categorical variables, such as ecoregion or climate zone, or with models that estimate changes as a result of biomass dynamics and disturbance history [7,20]. The IPCC provides guidelines for assessing these carbon pools, and there are several references available that summarize methods that are appropriate in different circumstances [4,5,8]. Descriptions of several different approaches for combining forest inventories with data from intensive sites (described later in this Review), including details of the data requirements and models used, are available for the three North American countries [21–23].

In the USA where there are data available from many ecosystem studies in different ecoregions and forest types, estimates of other forest carbon pools for the national GHG inventory have been made using a tier 2 approach [22]: carbon in standing dead trees and down dead wood is estimated using equations or ratios relating these quantities to live tree mass; and carbon in litter and soils is estimated with equations relating litter mass to stand age or time since disturbance. More recently, to move toward a tier 3 approach for these variables in the USA, carbon in standing dead trees and down dead wood has been estimated from inventory measurements of these variables on a subset of the national inventory sample plots [24]. The relative uncertainty of the different variable estimates for the USA suggests that the largest carbon pools – live trees and soil – contribute the most to the overall estimates of forest carbon stocks and stock changes, as might be expected [25]. The overall uncertainty of the estimated changes in forest carbon stocks for the USA is approximately 21% [26].

In tropical countries where sufficient field observations may be lacking, the IPCC recommends using generic emissions factors for tropical regions provided in their documentation (a tier 1 approach) but also recommends that such factors be developed with country-specific data where and when possible, to advance to a tier 2 approach [4,5]. However, it takes resources and time to implement the more intensive field studies required to represent the main ecoregions and forest types within a country.

In practice, forest inventories are often implemented with simple random sampling of an area or with a combination of remote sensing and field measurements using regression estimators, stratified sampling or two-phase sampling with regression estimators. A recent review paper compared these different sampling approaches to address the important issue of cost efficiency in the development of forest carbon stock assessments and the selection of remote-sensing techniques [27]. The authors recommended that implementation of monitoring systems for REDD+ should be based on an optimization process that compares different data sources and sampling designs, to reduce the costs and uncertainties.

To estimate changes in forest area, forest inventories may be combined with remote sensing; or changes in forest area may be estimated using only the proportion of field sample points that are classified as forest on the ground [28]. Regardless of the approach used, it is important to estimate both the gross gains and losses, and the net change. If only the net change is estimated, significant losses and gains of forest area, and the associated carbon emissions and removals, may not be revealed. Since REDD+ is concerned with both losses of forest land from deforestation and increases in forest land from agriculture reversions back to forest, full knowledge of these losses and gains is an essential component of a useful monitoring system for REDD+. Even if the area of forest land remains constant, biomass losses from deforestation can be substantially higher than biomass gains on new forest land, because biomass growth is slow compared with the rapid loss from harvesting.

Remote sensing for carbon monitoring

Here we briefly review the types and uses of remote-sensing for carbon monitoring and how remote sensing data is integrated with ground truth and models. A more in-depth overview of different remotely sensed and field measurements, and their capabilities and applications with respect to REDD+, is presented by Havemann [13].

Aerial photographs have been used for more than 80 years in forest inventories to estimate the proportion of land classified as forest in a given sampling area, and as a first-phase sample in a double-sampling strategy [29]. More recently, Landsat satellites have provided a time series of remotely sensed digital images spanning 30 years, and the images are now used widely for monitoring biomass and carbon stocks. Landsat data are particularly suitable for classifying vegetation and assessing attributes such as forest cover percent, leaf area index and disturbances, key variables for spatial ecosystem models and for estimating biomass [30]. Although Landsat imagery does not directly estimate biomass, spectral attributes are related to biomass and can be used in conjunction with field data and models to provide spatially explicit estimates of biomass and other vegetation attributes over large areas such as North America [31]. There are several approaches used to combine satellite data, models and field data for estimating biomass and biomass change [32,33,209]. These approaches involve using either empirical or **process models** (described later in this article) for integrating information that may include satellite data (e.g., land cover or Normalized Difference Vegetation Index), spatial data such as climate and topography, and field-based biomass estimates that are correlated with these variables and originally derived from the allometric relationships between biomass and frequently measured tree attributes.

The MODIS satellite has also had a long history of providing useful information about forest biomass, productivity and disturbances over large regions at coarse spatial resolution [34,35]. The daily temporal resolution yields more frequent cloud-free images that make this sensor particularly useful in tropical regions with persistent cloud cover [13]. One limitation of both Landsat and MODIS is that the passive optical signals 'saturate' at moderate-to-high levels of leaf area, so that these sensors cannot differentiate between ecosystems with moderate-to-high levels of biomass [36]. Landsat and MODIS are also unable to detect early regrowth of secondary vegetation, and do not reveal small disturbances such as removal of individual trees, which may be important for monitoring forest degradation.

Key terms

Empirical models: Describe the statistical relationship between observed variables or experimental data, and are approximate representations of the systems that generated the data. These models are typically used to describe the current state of a system or trends, and are sometimes used for making projections. An allometric equation (described above) is an example of an empirical model.

Process models: Often referred to as mechanistic models, explicitly represent an understanding of biological, chemical and/or physical processes, and attempt to quantify relationships among variables by their underlying casual mechanisms. Because of this mechanistic basis, process models are often considered to be better able to extrapolate relationships beyond the current or observed state, and may be particularly useful for making projections.

The detection limitations of Landsat and MODIS can be overcome by high-resolution optical sensors, aerial photographs and active sensors such as Light Detection and Ranging (LiDAR) or Synthetic Aperture Radar. Application of these remote-sensing instruments is currently limited to smaller areas because of the high volume of data and cost [13]. However, high-resolution sensors can be used to monitor individual trees or small disturbances, and have many uses in forest monitoring at smaller spatial scales. Synthetic Aperture Radar has the distinct advantage in tropical regions of penetrating clouds that mask the Earth from optical sensors, and can provide information about vegetation height and structure. Recently, LiDAR has gained popularity for high spatial resolution biomass estimation. LiDAR is an active optical sensor that can accurately measure vegetation height, does not saturate as quickly as Landsat under high-biomass conditions, and has been shown to be effective at estimating and mapping biomass at smaller scales, although when used as part of a sampling design such as strip sampling, may also be appropriate for large-scale estimation [37–39].

When using remote sensing for estimating changes in forest cover, it is important to distinguish 'forest cover' from 'forest land', which is typically reported by forest inventories and has a land-use connotation. From the forest inventory perspective, and as defined by FAO, forest land may include areas that are temporarily treeless as a result of harvesting or natural disturbance. This same land may be classified into a nonforest category from remote-sensing of land cover, and in a forest category from an inventory of forest land. The opposite is also true – the FAO forest definition does not include land that is predominantly agricultural or urban, even if such land has some tree cover. Failing to account for these differences can have a significant effect on the resulting estimates and make comparisons between different approaches confusing. For example, a recent study used MODIS and Landsat imagery to assess global forest cover loss, indicating that many areas were losing large amounts of forest cover; however, many of these areas were not considered to represent losses of forest land from the forest inventory perspective [40]. Many of the losses were temporary removals of trees followed by regrowth and not deforestation events.

The role of intensive monitoring sites

Even with advances in forest inventories and remote sensing, the uncertainty associated with estimation of CO_2 emissions and removals in the land use, land-use change and forestry sector remains relatively high because of the difficulties to estimate stocks and stock changes for all of the carbon pools. One way to overcome this limitation and to reduce the uncertainty is to have detailed information, generated at a fine scale in intensive monitoring sites, of:

- Carbon stocks and rates of change for carbon pools that may not be easily quantified over large areas by extensive field measurements;
- Processes of CO_2 uptake, sequestration and release to the atmosphere that can help explain observed changes that result from management or disturbance [41].

This information, in turn, can be used to develop emission factors or to parameterize models to scale-up estimates to regional and national levels when combined with remote sensing and national forest inventories.

Detailed information from intensive monitoring sites provides data about physiological parameters to develop and test models of carbon exchange, and to relate carbon fluxes to remote-sensing data. Physiological and ecological measurements on these sites allow separation of the components of carbon fluxes, such as CO_2 fixation rates, autotrophic and heterotrophic respiration, litter fall, decay rates of organic matter, and forest growth and mortality rates. These variables can reveal the mechanisms responsible for the fluxes, facilitate the use of models for the various uses in the assessment and reporting process, and design forest-management systems for increasing carbon stocks. Intensive monitoring sites provide data and information necessary to transition to higher tiers in MRV systems. These sites can also be valuable in cross-validation research through the testing of different MRV methods, and can provide or generate information for designing and implementing forest-management practices that can reduce emissions or increase carbon stocks at regional or state (province) scales. They also serve as centers for technology transfer and education centers for communities, and training for students, technicians and government personnel involved with forest ecosystem management.

Data collection and analysis of information from intensive monitoring sites is typically based on a hierarchical monitoring approach. Both 'bottom-up' and 'top-down' analysis approaches are combined across multiple spatial and temporal scales, with intensive and detailed studies providing specific information to scale-up through the use of remote-sensing techniques, extensive forest inventories (Table 1), and empirical and process modeling. Ideally, an intensive monitoring site should have three basic components, although the exact combinations of data collections and sampling designs are variable depending on site conditions and the objectives for establishing and maintaining the sites that may not be targeted specifically to improve estimates of carbon stocks and fluxes:

Table 1. Variables collected at each scale of analysis.

Variable	Intensive sites	Forest inventory	Remote sensing
Land cover	X	X	X
Leaf area index	X	X	X
Disturbance impacts	X	X	X
Aboveground biomass	X	X	X
Live and dead aboveground biomass	X	X	
Forest structure	X	X	
Species composition	X	X	
Growth, removals, mortality	X	X	
Forest health indicators	X	X	
Litter fall	X		
Belowground biomass	X		
Root dynamics	X		
Soil CO_2 flux	X		
Runoff	X		
Dissolved organic carbon	X		
Net ecosystem exchange of CO_2	X		
Energy and water balance	X		

Adapted from [41].

Ground plots

A dense network of ground plots for measurement of biomass and carbon stocks, and for monitoring carbon fluxes and growth and mortality rates. The plot layout should ideally follow the same protocol for sampling common variables as that used for national forest inventories to facilitate the consistency with field measurements following international standards. Analyzing the accumulation process of biomass and carbon in a network of plots in intensive sites will ensure that information collected represents ecosystems and forest types over a large region. Also, local estimation from ground plots will improve estimates of carbon accumulation and the upscaling processes when they are linked to data from national forest inventories.

Flux tower

A tower that extends above the forest canopy, instrumented to measure the exchange of water, energy and CO_2 between the forest and the atmosphere using a statistical technique known as 'eddy covariance'. A nondestructive technique, eddy covariance can be applied to timescales varying from minutes to years, and therefore is ideal to capture CO_2 fluxes across different climate conditions from diurnal cycles to long-term environmental changes [42,43]. The information generated by eddy covariance methods, coupled with extensive forest inventories and remote-sensed data into a data-assimilation framework [44], can be used to parameterize ecosystem models to support tier 3 reporting.

Remote sensing

A library of remote-sensing data from different sensors and resolutions, both spatial and temporal. Land cover and land-cover change are two variables that can be estimated with remote-sensing techniques, provide critical information about land-management activities and natural disturbances, and are fundamental to estimate emissions and removal of CO_2 at regional and national scales. Increasingly, stand structural information directly related to biomass estimation is becoming available from spaceborne and airborne sensors.

These components may be integrated into the MRV system using a variety of approaches – a few examples are provided here for illustration. A formal technique used to combine data and assess uncertainties from different studies that typically do not use the same methods is known as meta-analysis. This technique was used to quantify the effect of harvesting on soil carbon of temperate forests and it was found that, on average, harvesting reduced soil carbon by an average of 8 ± 3% (95% CI), with differences between forest types and soil layers [45]. Intensive sites having a broad suite of flux tower data and biometric measurements can result in comprehensive assessments of productivity, carbon allocation among pools and storage [46]. In developing such assessments, each individual measurement may have its own analysis method, and then the individual elements of the ecosystem carbon budget must be combined and their uncertainties estimated according to the understanding of relationships between physiological processes [46]. Data from eddy flux towers collected over a period of years or at several contrasting sites can reveal how annual carbon storage is simultaneously affected by multiple variables such as stand age, disturbance and climate [47]. The detailed measurements are used to parameterize empirical or process models, which can provide estimates or emission factors used by carbon accounting models [23].

Empirical & process models

One way to improve the precision and accuracy of estimates of carbon stocks and fluxes for the forest sector and their response to management, disturbances or climate is through the development, calibration and validation of carbon dynamics modeling tools for terrestrial ecosystems [48–50]. Models are powerful tools that enable the quantification of forest carbon dynamics through the synthesis and integration of data derived across different spatial and temporal scales, from detailed plot-level measurements to national-scale remote-sensing products [50–52]. Through these types of models we can understand the mechanisms controlling carbon exchanges between the land and atmosphere, identify gaps in information, and guide future research to fill in these gaps in a cost-effective manner [49,53,54]. Furthermore, models are the best tools available to create and compare scenarios to examine the effects of different activities on forest systems (e.g., management, land-use change and natural disturbances) that have not yet been observed [50,53].

Generally, the available models can be divided into those using detailed ecophysiological relationships between plants, soil and the atmosphere (process models), and those using information typically contained in forest inventories (empirical models). The first group of models requires information normally available at intensive monitoring sites such as leaf area index, interannual climatic variability and soil conditions, among other variables, to simulate carbon dynamics driven by photosynthetic processes (e.g., CENTURY, 3-PG, Biome-BGC) [55–57]. The second group of models uses information derived from forest inventories and management plans such as wood volume yield data (e.g., CBM-CFS3, CO2FIX) [50,58].

In order to make more reliable projections of carbon exchanges between vegetation and the atmosphere, and to determine the magnitude and direction of the response of forest ecosystems to global change, the combination of both modeling approaches may be necessary, taking advantage of the strengths of each [23,59]. Process models are more useful for simulating forest ecosystem response to changes in climate or in the concentration of atmospheric CO_2, and may be used to make estimates or projections outside the spatial and temporal boundaries of the data used for parameterization. Empirical models are well suited to represent carbon stock changes of the different carbon pools due to: impacts from management activities, fires, pests and land-use change; to quantify the uncertainty of directly measured carbon pools; and to validate the independent estimates from process models [23,50]. Conversely, it is important to validate process models with independent datasets before attempting to use them outside the range of parameterization data, and using empirical models to extrapolate in time and space should be done cautiously and with acknowledgement of possible sources of error or bias such as failure to account for rising CO_2 concentrations or changes in growing season length.

The Good Practice Guidelines of the IPCC recommend that the uncertainties associated with the estimation of GHG emissions and removals within forest ecosystems are identified, quantified and reduced as far as practicable [4]. According to the IPCC, the uncertainty of model-based estimates reflects the degree of lack of knowledge that exists about the processes that generate GHG fluxes [5]. Thus, countries seeking to use models to assess forest carbon dynamics must quantify the level of reliability of the results by examining the effects of model structure and model inputs on the variability in the estimates of GHG fluxes [60]. For example, they must have an adequate quality control system to test for errors in model structure or coding, and to determine if the input data were collected and/or processed improperly, if there are errors from an inadequate adaptation of the model in a different domain of origin, or if the scientific assumptions that determine the logic of the study processes are not correct [53].

Currently, only Canada (i.e., CBM-CFS3) [23,50] and Australia (i.e., FullCAM) [61] use models as the primary basis for the preparation of national reports for their forestry sectors [53]. However, exploration of modeling approaches is beginning to spread to several countries, including some in the tropics (e.g., Mexico, Indonesia) [62,63]. In the case of many tropical countries, substantial efforts are required to generate sufficient experimental and observational data (e.g., rates of biomass growth and transfers to soil compartments, decomposition rate of organic matter in soil) to calibrate key parameters and validate modeling results at regional or national scales. Nevertheless the use of modeling tools can still be valuable for improving monitoring and reporting of GHG dynamics in these countries. If based on the best available scientific and technical information, models can help understand past GHG emissions and removals, identify key contributors to the GHG net balance (human or natural) and estimate the impact of specific policy-mitigation activities (e.g., REDD+) on future GHG emissions and removals dynamics [64].

An important use of models in proposed MRV systems is to establish forward-looking reference levels or baselines. Generally, a reference level is defined as a *"benchmark scenario against which future emissions reductions can be measured"* and *"are used to determine the additionality of a given activity"* [65]. The baseline is a critical determination, since in a carbon crediting system credit for additions to carbon stocks may be given only for the amount that exceeds the expected baseline. Although baselines may be defined as an observed historical trend or even a point in time, a baseline may also be defined as an expected change in carbon stocks under a scenario that may reflect current policies and management practices, or include changes that may be expected compared with historical references. Estimating a project baseline may be complicated and require consideration of many factors [66]. However, in most cases it is necessary to quantify the changes in carbon stocks that are likely in the future, requiring an ecosystem modeling approach as described in this section.

Integration of approaches: moving from tier 1 to tier 3

▪ Spatially explicit & spatially referenced methods

IPCC methodologies outline two possible methods for estimating and reporting GHG emissions and removals in the land use, land-use change and forestry sector [4,5]. The spatially explicit and spatially referenced methods differ in the way in which information about land characteristics and human activities is compiled and used in the estimation and reporting of GHG dynamics. Spatially explicit methods require that all information is available for each land cover polygon (or pixel) with complete (wall-to-wall) coverage of all relevant land areas. Spatially referenced approaches define the geographic boundaries within the country for which estimates are calculated and reported such as states, provinces or ecoregions. Spatially referenced methods are more suitable for countries that rely on sampling approaches in the development of GHG inventories. For example, information from forest inventory sample plots for specific geographic strata (or reporting regions) can be extrapolated to the entire reporting region. Depending on the national circumstances and available resources, either of these methods can be implemented in an MRV system, and it is also possible to mix the approaches, using spatially referenced methods where data are sparse and spatially explicit approaches for specific areas of greater interest or with higher rates of human activities.

Spatially explicit methods typically require information on land cover and land-cover changes obtained from time series of remote-sensing products [40,67]. The land-cover class prior to disturbance, the year and type of disturbance, and where available the postdisturbance land-cover class information for each polygon in the landscape, can be combined with data on forest carbon dynamics to estimate carbon stocks, stock changes, and the associated emissions and removals over time. Such approaches are data and computationally intensive, and are typically constrained by the small number of land-cover classes that can be identified in remote-sensing products and the associated errors in classification [68]. Methods that base change detection on more than two images or scenes, and taking account of phenological differences, can reduce uncertainties of change products [69].

Spatially referenced methods can be based on remote sensing or sample-based information. For example, countries can develop annual (or periodic) land-cover change matrices that define, for a specific region, the annual rates of change among land-cover classes. Some of these transitions are associated with human activities that are defined as deforestation or degradation events, while other transitions are the result of forest establishment or postdisturbance recovery. Quantification of the carbon implications of these transitions can then contribute to GHG budgets. Lower tier methods are typically based on simple emission factors that characterize the emissions associated with specific land category transitions. Tier 3 methods involving models account for more complex pre- and post-disturbance carbon dynamics.

The use of spatially explicit methods is often limited by availability of historical spatially explicit data or interpretations of historical satellite data for mapping of attributes such as deforestation or wildfire. Likewise, some models may not operate in spatially explicit modes. In contrast, spatially referenced methods lack the ability to provide estimates at spatial scales smaller than geographic regions or ecoregions. Both methods should include quantification of errors and an assessment of the minimum area for which estimates can be used with some specified level of precision. Both methods require additional tools that translate the information about forest conditions, changes in forest conditions and the associated rates of human activities into estimates of GHG emissions and removals. This can be done with elaborate spreadsheet systems, or carbon budget models that deploy empirical or process-based simulation of forest (and other land category) carbon dynamics, as discussed above.

Spatially referenced methods are more readily useable for the development of projected 'business-as-usual' or reference levels required for the implementation of REDD+ programs for payment of emission-reduction achievements. Models that use historic data on human activities such as deforestation, degradation and forest management can project such rates of activities into the future using various assumptions about rates of

Key term

Imputation methods: Refers to the process of replacing missing data with substituted values. After the missing values have been imputed, the resulting dataset may be analyzed using techniques for complete datasets, although bias may be introduced by the imputation process. There are many imputation methods and they are constantly evolving. A typical method used in forestry is the k-nearest neighbor method, used to produce continuous maps of forest attributes based on empirical relationships between variables determined at sample points, extrapolated to a grid of cells across a large landscape.

change. It is much easier and more efficient to develop such scenarios using a spatially referenced framework because it is not necessary to account for the spatially explicit details of where and when the various activities might occur in the future. Some models can use spatially explicit information to characterize past changes, for example from 1990 to the present, and then use spatially referenced information for the projection of future GHG budgets [23].

Combining & comparing remote sensing, field data & modeling

Combining and comparing estimates from different approaches is a useful way to reduce costs, improve or gain confidence in the results, if the estimates from different approaches are similar. Comparison studies may also help with understanding the causes of differences in order to improve comparability of results in the future. Comparisons may take many different forms – here we use examples to illustrate two kinds of comparisons that are particularly relevant to implementing a REDD+ system: combining LiDAR remote sensing with field data to estimate above-ground carbon density, and comparing large-scale remote-sensing biomass maps with landscape-scale field data.

Mapping and monitoring carbon stocks is an important element of preparing for REDD+, and there is a growing interest in using remote-sensing-based methods, of which there are many different approaches [70]. A recent study evaluated two approaches to calibrate airborne LiDAR data with ground-based forest inventory plots [37]. One approach involved field measurements of tree species, diameters and heights, which were combined into an allometric model of tree height as a function of tree diameter that is regionally appropriate for calibrating the LiDAR data after also taking account of wood density. Another more universal approach involved relating LiDAR mean canopy height to field-measured basal area, and using regional average wood densities to reduce the time needed to collect data in the field. This simpler approach accurately predicted aboveground carbon density ($r^2 = 0.80$; root mean square error = 27.6 MgC ha^{-1}).

Recent research has developed a high-resolution continental-scale biomass map for the USA [26], and similar maps have been developed for most of the tropics [71,72]. The US map was based on an empirical modeling approach to combine US Department of Agriculture Forest Service Forest Inventory and Analysis data with high-resolution radar data and optical remote-sensing data acquired from the Landsat ETM+ sensor. We compared this map with small (1 km^2) landscape-scale areas where we had independently estimated above-ground woody biomass using a dense network of field plots (Figure 1) [73]. The comparison showed that the map performed well across a range of biomass densities, with a slight tendency to underestimate biomass in high-density areas, which is likely the result of the saturation effect described earlier.

Imputation methods

There is yet another approach to the estimation and mapping of forest carbon, via **imputation methods**, that incorporates information collected from national forest inventories, remote sensing and other auxiliary data, as well as empirical models. In general, imputation is a technique for replacing missing data in a collection with substitute data. There are many possible rules for performing this substitution, but in the case of the approach described here, the rule is based on using one or more substitute data points that are in some way most similar to the missing data point. This is typically referred to as nearest-neighbor imputation, a methodology that is increasingly being used to fill in missing data at a sample plot or polygon level [74]. For national forest inventory applications, this technique has been used extensively in Finland [75] and the USA [76,77]. Similar approaches have also been used with LiDAR data [78,79].

In the context of mapping and estimation of forest carbon stocks, one application of the nearest-neighbor imputation methodology integrates field plot data with tree- and plot-level models of forest carbon pools, MODIS imagery, ecological zone boundaries, as well as climatic and topographic raster data [80,81]. These data were used to construct a model that relates the response variable collected from the field to the predictor auxiliary variables. The model coefficients were used to transform the predictor variables into a new set of variables. The transformed variables specified by the model were used to conduct nearest-neighbor imputation of plots to pixels. Each transformed variable can be thought of as one dimension in a new coordinate space. Each pixel in the predictor dataset can be located in this new coordinate space. Each field plot can likewise be located in this space, based on the pixel where it is geo-located. In this imputation scenario, the missing data are the modeled forest carbon data for all of the pixels that do not contain plots. The substitution data are the data derived from the empirical forest carbon stock models for the field plots that were collected. Each pixel is then assigned the value, or average value, of the attribute of interest from the plot, or a small set of plots, nearest to it in the transformed coordinate space.

Estimates are then computed by adding up imputed pixel values within the estimation area of interest.

To date, this particular approach has been used only in the USA in temperate and subtropical forests using an extensive network of permanent plots collected under a quasi-systematic sampling design. The robustness and feasibility of using this approach in the tropical forests of Latin America has not been tested, particularly in countries with restricted access to the forested estate requiring the use of unequal probability sampling, nor in countries with limited funding for an extensive plot network.

Uncertainty of imputed results may be assessed in several ways. One approach is to validate the results using independent datasets at different spatial scales using various statistical metrics to test the agreement between the datasets [80]. This approach can produce both cumulative distribution functions of map-based versus field-based estimates of carbon stocks and choropleth (or shaded) maps that indicate the confidence level of estimates as well as indicating whether the map estimate is higher or lower than the field estimate. In general, however, the statistical foundation for imputation techniques is not very well developed, and this is an active area of research [82].

MRV options & range of choices for countries

A country's choice of an MRV strategy will generally depend upon a combination of factors, including historic patterns of forest cover change, current landscape composition, demographic trends, available budgets, institutional readiness and labor costs. The former three factors will particularly affect strategic MRV components such as definition of forest and establishment of reference emissions levels [83], whereas the latter three will tend to affect tactical components such as the choice of remote-sensing methods and ground data acquisition strategies [84,85]. Countries proposing an MRV system should take the unique combination of these factors into account.

When considering an MRV system proposal for carbon monitoring, it can be helpful to consider the MRV system in the context of a broader vision for natural resource monitoring. From this perspective, one can consider the development of a natural resource-monitoring system as being a process of continually assessing information needs and improving estimates by reducing uncertainty. Guidance provided by the IPCC in the form of the tier system can be helpful in this respect [4,5]. Figure 2 provides a conceptual model of the evolution of a natural resource-monitoring system, of which an MRV is a component. This model is highly compatible with the tier system, and can serve as a tool with which countries can assess the mix of factors that affect their choice of a strategy.

Key points to take note of in Figure 2 are that, first, it represents an approach that progresses towards increasing scientific validity and reduced uncertainty of estimates.

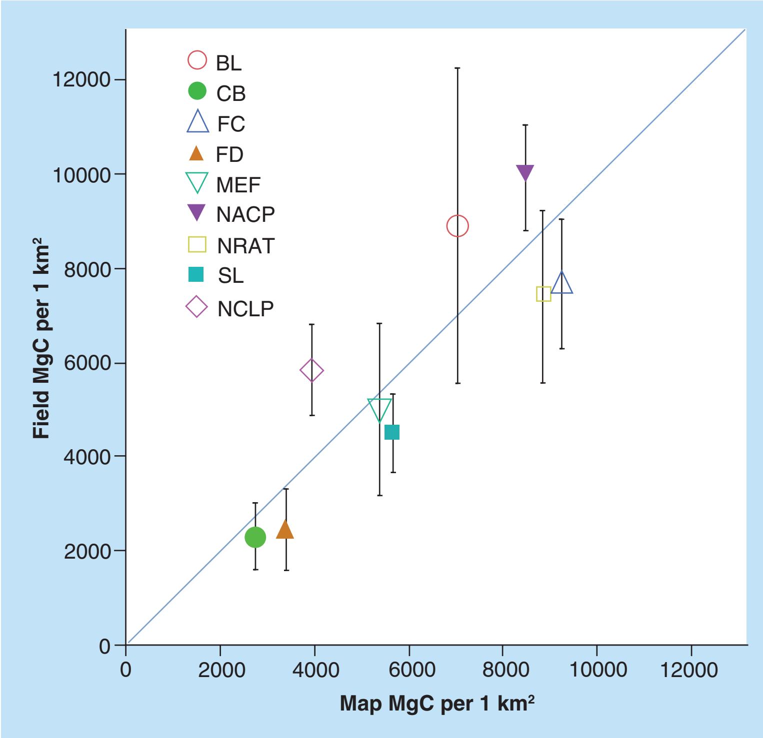

Figure 1. The total aboveground biomass carbon (tree and sapling) for nine intensive monitoring sites of 1 km² compared with the values extracted from a biomass map over the same area [209]**.** The totals represent the mean of 12–16 plot measurements within a 1-km² area and scaled to 1 km². The error bars are the 95% confidence limits of the mean biomass carbon of each site after applying error-propagation methods scaled to 1 km² [90].

Symbols represent field sites: BL: Brooklyn Lake, WY, USA; CB: Cedar Bridge, NJ, USA; FC: Fool Creek, CO, USA; FD: Fort Dix, NJ, USA; MEF: Marcell Experimental Forest, MN, USA; NACP: Bartlett Experimental Forest, NH, USA; NCLP: North Carolina Loblolly Pine Parker Tract, NC, USA; NRAT: Niwot Ridge Ameriflux Tower, CO, USA; SL: Silas Little, NJ, USA.

Each country, based on a range of factors, might choose a particular set of methods when it is necessary to have results to meet reporting requirements. Second, it assumes that forest inventory data from an inventory design based on sampling theory constitute a 'gold standard'. This perspective arises from guidance from the IPCC [4,5], and is due to the fact that well-designed surveys have been used for decades to generate information that can be interpreted through the lens of sampling theory, which provides a common, well-understood language for resource professionals to use to help make decisions. Furthermore, integrating an MRV with an existing natural resource-monitoring strategy (one that necessarily includes some form of statistically valid forest inventory) is more efficient than having the MRV and the inventory decoupled. Third, remote sensing is a critical component of any MRV system, particularly in areas where the costs of field plots

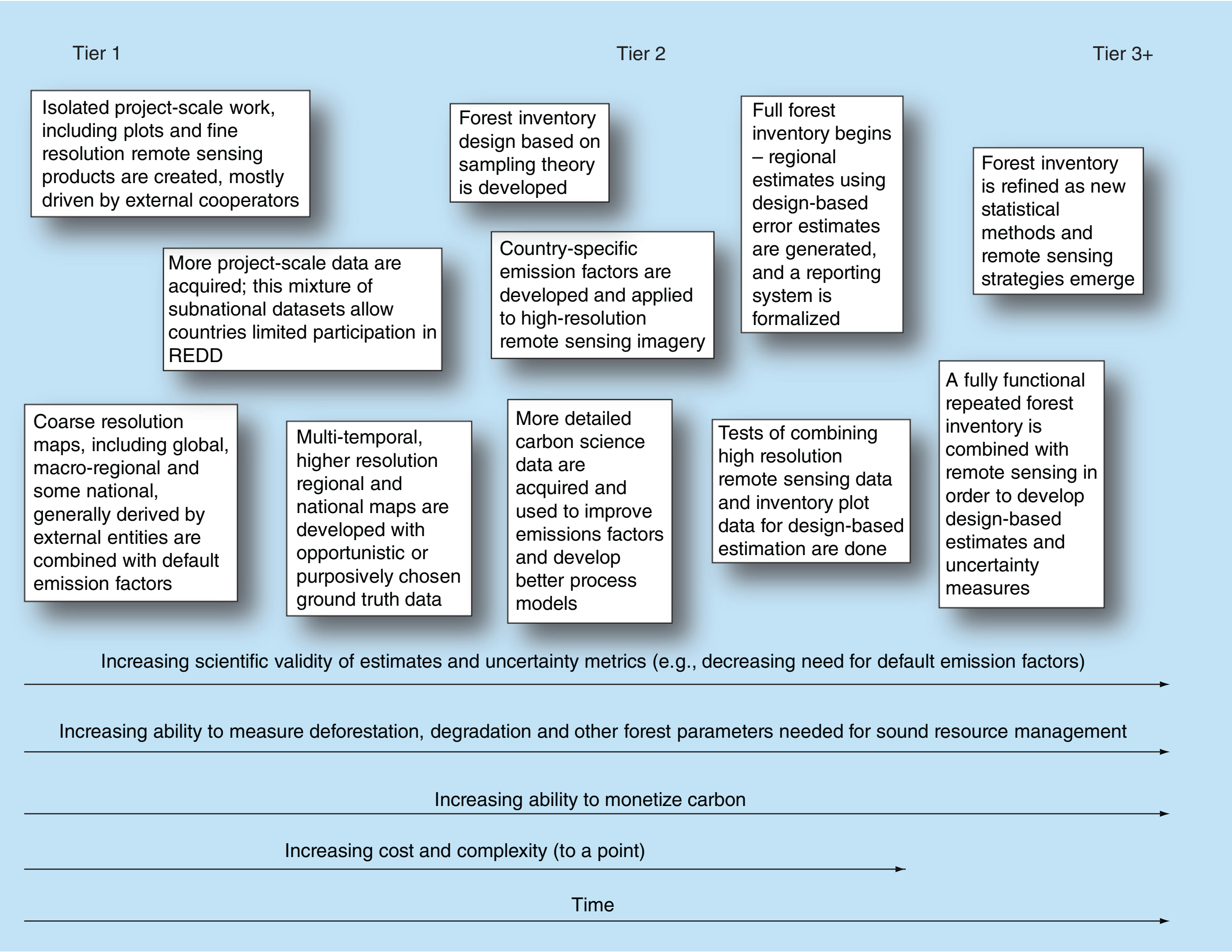

Figure 2. Conceptual model of the evolution of a measurement, reporting and verification system. Milestones in this process are indicated, with relative locations along the continuation of time, cost, value, usefulness and quality shown.

are high. The specific mixture of remote sensing and design-based inventory plots a country chooses will again result from an analysis of opportunity costs.

The different pathways and end products identified in Figure 2 are associated with different types of uncertainty metrics. These uncertainty metrics will have different levels of acceptance by groups or panels evaluating an MRV system. In principle, higher tier end products with well-defined uncertainty metrics will lead to higher carbon payments than those based on weaker foundations. Countries need to take this into account and balance the opportunity costs when choosing the desired combination of tier and uncertainty level, all in the context of their own institutional readiness.

In conclusion, it is important to recognize that a country's unique circumstances should dictate where in the evolutionary process to begin the implementation of an MRV system. Of particular concern are cases where donors attempt to promote an MRV system that is not compatible with a country's institutional readiness, or one that does not consider that an MRV could be a component of a broader resource-monitoring system, which includes some combination of national forest inventory plots and remote sensing. Finally, regardless of current economic conditions, the MRV should be created with a vision in mind (e.g., Figure 1), and that, ultimately, higher tier reporting corresponds to higher capacity to monetize carbon and generate a more effective and scientifically defensible natural resource-monitoring program.

Methods for estimating & reporting uncertainty

Estimating uncertainty is a valuable tool for a variety of reasons. Principally, the process of quantifying the confidence in estimates helps policymakers and forest managers to better understand how much confidence to place in the results when making decisions. Uncertainty estimates also can be used to prioritize efforts to improve the accuracy in carbon stock estimates and informs decisions on methodological choices for estimating carbon stocks [86]. In a REDD+ context, estimates need to be credible to the community at large with sufficient accuracy before any payments can be made. Quantification of uncertainty, showing the upper and lower confidence limits, would allow for REDD+ projects to be acceptable since the principle of conservativeness could be applied to adjust carbon numbers to the lower limit to ensure an overall reduction in CO_2 [87]. However, it is also possible that large uncertainties could overwhelm any improvements, so that no payments are made.

Uncertainty can be thought of as errors, unreliability, inexactness and imperfection in the knowledge of an estimate or process [88]. Some common sources of uncertainty stem from natural variability, measurement errors, the use of sampling statistics, lack of representativeness and model form, use and parameter estimates, and human errors in data processing. In complex systems it is difficult or impossible to completely quantify and characterize all the uncertainties, but measurement error and natural variability (sampling error) are the most rigorously quantified in ecology [89,90].

Uncertainty analysis is the process of quantifying uncertainty in an estimate or model, and determines the relative degree of importance in the various sources of error [88,91,92]. Error propagation of the individual uncertainties is part of the process to estimate the overall uncertainty in an estimate, and can be done explicitly or through the use of Monte Carlo analyses. Table 2 shows a summary of the most common approaches to uncertainty analysis.

Countries eligible for participation in REDD+ know they need to implement strict quality assurance procedures in all steps of the data collection and estimation processes, and quantify uncertainties. However, as an example, at a recent meeting of tropical countries in Latin America, only one country out of eight had begun work on quantifying uncertainties in their estimates [93,210]. There was general agreement that uncertainty quantification was a priority, but most efforts are directed at other areas of MRV. A perception that quantifying uncertainty is difficult and that their uncertainties are high compared with what will eventually be required under REDD+ placed emphasis on these other areas. Reluctance to perform uncertainty analysis is based on a variety of other reasons [94].

Conclusion

Monitoring changes in forest carbon and attributing those changes to specific human activities and natural factors will continue to be a challenge in the coming decade. The basic elements of MRV – field inventories, remote sensing, intensive monitoring sites and models – are available now and improving over time, but their application must still be tailored to individual country circumstances, the unique characteristics of different forest ecosystems, and the driving factors that influence their carbon stocks. With climate changing and new programs being designed to mitigate the buildup of CO_2 in the atmosphere, it will be a continuing challenge to keep pace with the demands for basic information and the means to assimilate available data into meaningful analyses that can separate the different causes of observed effects. Even with the emergence of advanced space-based and aerial observation instruments, good field data is essential but often lacking in many tropical regions, despite international efforts to fill these gaps. Nonetheless, the last decade has witnessed a significant escalation of deployment of the MRV elements, and there is reason to expect that this trend will continue along with advancement in analytical tools such as ecosystem models that can make good use of the increasingly available data.

Future perspective

The main elements of current monitoring systems such as Landsat satellites and traditional forest inventories will continue to be the backbone of many forest-monitoring systems around the world. However, new technologies and monitoring approaches are addressing problems specific to the tropics and implementing REDD+. LiDAR techniques are becoming widely deployed to improve knowledge of vegetation structure, which combined with field observations can address the need for information about aboveground carbon pools at field sites and improve estimates of changes such as forest degradation. Although it is expensive to acquire LiDAR imagery over large areas, sampling approaches based on LiDAR flight lines show great promise [39]. There is no current satellite system delivering 3D imagery, but NASA's 'ICESat-II' with an orbiting laser altimeter is scheduled for launch in 2016, and Japan has a planned 2013 launch of ALOS-2, which includes a radar instrument. Both of these will enhance our capacity to map and monitor dynamics in forest structure. High-resolution optical sensors such as RapidEye are being tested for use over large areas [95], and radar has gained increasing attention because of its ability to penetrate clouds [96]. Studies of forest species composition at landscape scales using hyperspectral imagery have shown great promise for improving knowledge of ecosystems [97]. Although the Hyperspectral Infrared Imager developed by NASA has no planned launch date, the European Space

Table 2 Approaches to uncertainty estimation.

Approach	Description	Advantages	Disadvantages	Ref.
Expert opinion	Experts in the area provide their best judgment as to the numerical level of uncertainty based on their experience. The process involves surveying a number of experts and compiling the information in a systematic manner to produce a quantified uncertainty	Where uncertainty estimates do not exist, this approach permits the identification of priority areas on which to focus on gathering more complete information. It is a simple and straightforward process	Sufficient expertise may not be available. Uncertainty estimates are less credible and generally high	[86]
Classical	Standard frequentist approach that examines probabilities of estimates to be different from the 'true' value where inferences can be made about the population from sample data	Widely known method. Results are familiar to most persons. Vast amount of literature available on methods. Considered to be the best available and most robust methodology	Requires assumptions about data and population distributions that are not always met (normality, homoscedastic and so on). For reducing levels of uncertainty, the approach often requires large sample sizes	[86]
Monte Carlo	Uses the selection of random values from within individual PDF to calculate a value. The calculation is run numerous times using different selections of random variables to develop the overall probability density function	Can be performed at many levels of estimation. Can use with PDFs of any physically possible shape and width. Straightforward process to implement and propagate errors. Easiest approach where a classical approach cannot be used	Can be computationally intensive. Requires the analyst to have scientific and technical understanding of the data. Analyst must choose a PDF for each variable and outcomes are heavily influenced by this choice	[86]
Bayesian	Uses the Bayes Theorem and some form of Monte Carlo method (often Markov Chain Monte Carlo) to generate PDFs based on prior information and data	Allows the incorporation of any prior information of PDFs to inform posterior PDFs and therefore reduce uncertainty. Can be used to estimate uncertainty in complex models	Is not listed as an approved method in IPCC guidance documents. Not widely known	[107,108]

PDF: Probability density functions.

Agency has planned a 2014 launch of Sentinel-2 with 13 spectral bands.

Expanded networks of field-monitoring sites are especially needed in the undersampled tropical forests of the world [13]. Regional or global networks have emerged to address this need on an opportunistic basis, depending on local collaborators to identify monitoring sites. For example, the RAINFOR network is a series of long-term sites monitoring forest dynamics across Amazon forests [98], and the Global Ecosystem Monitoring network aims to measure and understand forest ecosystem functions and traits [99], although the areas sampled are targeted to intact Amazonian forests and are not representative of the range of forest conditions in the region. Nonetheless, these sites are essential for monitoring the annual changes in forests from disturbances such as storms and drought, and are usually the only source of information about carbon pools that are not typically measured in forest inventories, such as soil, belowground biomass, litter and understory vegetation.

There is steadily increasing recognition of the utility of combining remote-sensing measurements with field data, and these approaches continue to evolve as new sensors are deployed and as the availability of field data increases. Individually, both approaches have limitations: field measurements can only sample a small fraction of the domain, while remote-sensing techniques grapple with varying sensor angles, atmospheric properties, physical constraints and technological change, resulting in a limited number of observable attributes (Table 1). Approaches for landscape scale and larger area estimation of forest biomass and carbon need to be flexible enough to accommodate different field-sampling schemes, types of remote sensors and empirical models used to interpret them [84,100].

There is great room for improvement in methods to scale up precise, locally replicated measurements to ecoregion, national, continental and biome estimates, especially in areas that are challenging to sample on the ground such as mangrove forests. Scaling up will clearly benefit from the more sophisticated maps of forest area and attributes becoming available from advanced remote sensing, as well as improvements in the models used to integrate these sources of information [101,102].

For understanding processes and projecting future forest conditions, dynamic global vegetation models simulate both forest distribution and ecosystem biogeochemical cycles, and are becoming more widely used as global data availability improves [103,104]. A new class of models employs a technique known as 'perfect plasticity approximation', which provides a methodology for scaling up properties from individual trees to whole populations, to allow inclusion of the effects of changes in species composition and competition within the plant functional types typically used by dynamic global vegetation models [105]. These newly evolving models can simulate spatially explicit global or landscape-scale vegetation dynamics and feedbacks of carbon and water exchanges to the atmosphere under past, current or future climate, and may be useful in the future for establishing baselines and separating the influence of various driving factors such as land management, changing climate and rising CO_2 concentration [106].

Finally, it is important to recognize the importance of standardization and consistency of approaches and specifications of reporting requirements, while allowing the necessary flexibility for participation by all countries, taking account of individual country circumstances. The ability to compare methods and data across regions is a vital aspect of improved monitoring of forest carbon in support of REDD+.

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Executive summary

Monitoring & reporting requirements for REDD+

- Monitoring programs to support REDD+ are still evolving as countries grapple with implementing the appropriate methods in varying national circumstances. Countries are encouraged to use the best possible methodology appropriate to their national circumstances and to improve estimates over time.

Elements of approaches

- National forest inventories can be the foundation of forest carbon monitoring, either as an initial inventory of stocks from which changes can be estimated, or as a direct estimate of stock change from repeated inventories. National forest inventories are particularly suitable for monitoring key elements of forest dynamics (growth, harvest, mortality), and for estimating biomass of trees and forests.
- The Landsat satellites have provided a time series of remotely sensed digital images spanning 30 years and are now being used widely in monitoring activities such as deforestation, forest degradation and natural disturbances, and for estimating changes in biomass and carbon stocks.
- For estimating changes in forest area from deforestation and afforestation, it is important to estimate both the gross losses and gains, and the net change. If only the net change is estimated, significant losses and gains of forest area and the associated carbon emissions and removals may not be revealed.
- Detailed information generated at a fine scale at intensive monitoring sites can address the difficulty of estimating stocks and stock changes for litter, dead wood and soil, and for developing model parameters.
- Models are powerful tools that enable the quantification of forest carbon dynamics through the synthesis and integration of data across different spatial and temporal scales, and are the best tools available to create and compare future scenarios to examine the effects of different activities (e.g., management, land-use change and natural disturbances).

Integration of approaches: moving from tier 1 to tier 3

- Implementation of monitoring systems for REDD+ should be based on an optimization process that compares different data sources and sampling designs, to reduce the costs and uncertainties. The process of quantifying the confidence in estimates helps prioritize efforts to improve the accuracy in carbon stock estimates.
- A country's choice of a measurement, reporting and verification strategy will generally depend upon a combination of factors, including historic patterns of forest cover change, current landscape composition, demographic trends, available budgets, institutional readiness and labor costs.

Future perspective: technology of future monitoring approaches

- The main elements of current monitoring systems such as Landsat satellites and traditional forest inventories will continue to be the backbone of many forest-monitoring systems around the world, but new technologies and monitoring approaches are addressing problems specific to the tropics and implementing REDD+.
- Light Detection and Ranging techniques are becoming widely deployed to improve knowledge of vegetation structure, which combined with field observations, can address the needs for information about aboveground carbon pools.
- Expanded networks of field-monitoring sites are especially needed in the undersampled tropical forests of the world. Regional or global networks have emerged to address this need on an opportunistic basis, depending on local collaborators to identify monitoring sites and to provide their data.
- For understanding processes and projecting future forest conditions, new classes of dynamic vegetation models are emerging to simulate forest distribution, forest dynamics and ecosystem biogeochemical cycles.

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References

Papers of special note have been highlighted as:
- ▪ of interest

1 Pan Y, Birdsey RA, Fang JY *et al.* A large and persistent carbon sink in the world's forests. *Science* 333(6045), 988–993 (2011).
- ▪ **Presents a compilation of the world's forest inventory data and the contribution of tropical forests to the global carbon budget.**

2 Nabuurs GJ, Masera O, Andrasko K *et al.* Forestry. In: *Climate change 2007: Mitigation of Climate Change.* Metz B, Davidson OR, Bosch PR, Dave R, Meyer LA (Eds). Cambridge University Press, Cambridge, UK, 541–584 (2007).

3 Hiepe C, Hideki K. *Review of Literature on Monitoring to Support REDD.* UN-REDD Programme, Geneva, Switzerland (2008).

4 IPCC. *Good Practice Guidance for Land Use, Land-Use Change and Forestry.* Institute for Global Environmental Strategies, Hayama, Japan (2003).

5 IPCC. *IPCC Guidelines for National Greenhouse Gas Inventories. Volume 4 Agriculture, Forestry and Other Land Uses.* Institute for Global Environmental Strategies, Hayama, Japan (2006).

6 Munoz-Pina C, Guevara A, Torres JM, Brana J. Paying for the hydrological services of Mexico's forests: analysis, negotiations and results. *Ecol. Econ.* 65(4), 725–736 (2008).

7 Birdsey RA, Heath LS. Forest inventory data, models, and assumptions for monitoring carbon flux. In: *Soil Carbon Sequestration and the Greenhouse Effect.* Lal R, Follett RF (Eds). Soil Science Society of America, Inc., WI, USA, 125–135 (2001).

8 Pearson TRH, Brown SL, Birdsey RA. *Measurement Guidelines for the Sequestration of Forest Carbon.* US Department of Agriculture Forest Service, PA, USA (2007).

9 Phillips DL, Brown SL, Schroeder PE, Birdsey RA. Toward error analysis of large-scale forest carbon budgets. *Glob. Ecol. Biogeogr.* 9, 305–313 (2000).

10 Heath LS, Smith JE, Skog KE, Nowak DJ, Woodall CW. Managed forest carbon estimates for the us greenhouse gas inventory, 1990–2008. *J. Forestry* 109(3), 167–173 (2011).

11 Woodall CW, Domke GM, Macfarlane DW, Oswalt CM. Comparing field- and model-based standing dead tree carbon stock estimates across forests of the US. *Forestry* 85(1), 125–133 (2012).

12 FAO. *Global Forest Resources Assessment 2010. Forestry Paper 163.* FAO, Rome, Italy (2010).

13 Havemann T. *Measuring and Monitoring Terrestrial Carbon: The State of the Science and Implications for Policy Makers.* FAO, UN-REDD Programme, Geneva, Switzerland, 67 (2009).

14 Woodall CW, Heath LS, Domke GM, Nichols MC. *Methods and Equations for Estimating Aboveground Volume, Biomass, and Carbon for Trees in the U.S. Forest Inventory, 2010.* US Department of Agriculture, Forest Service, Northern Research Station, PA, USA (2011).

15 Zianis D, Muukkonen P, Mäkipää R, Mencuccini M. Biomass and stem volume equations for tree species in Europe. *Silva Fennica Monographs* 4, 63 (2005).

16 Brown S. *Estimating Biomass and Biomass Change of Tropical Forests: A Primer.* FAO, Rome, Italy (1997).

17 Jenkins JC, Chojnacky DC, Heath LS, Birdsey RA. National-scale biomass estimators for United States tree species. *Forest Sci.* 49(1), 12–35 (2003).

18 Chave J, Andalo C, Brown S *et al.* Tree allometry and improved estimation of carbon stocks and balance in tropical forests. *Oecologia* 145, 87–99 (2005).
- ▪ **Excellent summary of the state of the art for developing generic biomass equations for use in the tropics.**

19 Clark DA, Brown S, Kicklighter D, Chambers JQ, Thomlinson JR, Ni J. Measuring net primary production in forests: concepts and field methods. *Ecol. Appl.* 11, 356–370 (2001).

20 Kurz WA, Apps MJ. Developing Canada's national forest carbon monitoring, accounting and reporting system to meet the reporting requirements of the Kyoto Protocol. *Mitig. Adapt. Strat. Glob. Change* 11, 33–43 (2006).

21 Ministry of Environment and Natural Resources, National Institute of Ecology. *Fourth National Communication of Mexico to the United Nations Framework Convention on Climate Change.* National Institute of Ecology, Mexico City, Mexico (2011).

22 Smith JE, Heath LS, Skog KE, Birdsey RA. Methods for calculating forest ecosystem and harvested carbon with standard estimates for forest types of the United States. US Department of Agriculture Forest Service, PA, USA (2006).
- ▪ **Collection of methods used to convert data from forest inventories and intensive-site studies into coefficients useful for estimating carbon for different forest components.**

23 Stinson G, Kurz WA, Smyth CE *et al.* An inventory-based analysis of Canada's managed forest carbon dynamics, 1990 to 2008. *Glob. Change Biol.* 17(6), 2227–2244 (2011).
- ▪ **Canadian example of an operational forest carbon monitoring system at the national scale that makes use of all the major components of a measurement, reporting and verification system.**

24 Woodall CW, Domke GM, MacFarlane DW, Oswalt CM. Comparing field- and model-based standing dead tree carbon stock estimates across forests of the US. *Forestry* 85(1), 125–133 (2012).

25 Heath LS, Smith JE. An assessment of uncertainty in forest carbon budget projections. *Environ. Sci. Policy* 3, 73–82 (2000).

26 US EPA. *Inventory of U.S. Greenhouse Gas Emissions and Sinks: 1990–2010.* US EPA, Washington, DC, USA (2012).

27 Köhl M, Lister A, Scott CT, Baldauf T, Plugge D. Implications of sampling design and sample size for national carbon

accounting systems. *Carbon Balance Manag.* 6(1), 10 (2011).

28 Van Deusen PC, Roesch FA, Wigley TB. Estimating forestland area change from inventory data. *J. Forest.* 111(2), 126–131 (2013).

29 Gregoire TG. Roots of forest inventory in North America. In: *Proceedings of the National Convention: A-1 Inventory Working Group, Society of American Foresters.* Bethesda, MD, USA (1993).

30 Cohen WB, Goward SN. Landsat's role in ecological applications of remote sensing. *Bioscience* 54(6), 535–545 (2004).

- **Excellent review of the different applications of data from the longest operating series of remote-sensing satellites – Landsat.**

31 Cohen WB, Harmon ME, Wallin DO, Fiorella M. Two decades of carbon flux from forests of the Pacific northwest. *Bioscience* 46(11), 836–844 (1996).

32 Potter C, Gross P, Klooster S, Fladeland M, Genovese V. Storage of carbon in US forests predicted from satellite data, ecosystem modeling, and inventory summaries. *Clim. Change* 90(3), 269–282 (2008).

33 Powell SL, Cohen WB, Healey SP *et al.* Quantification of live aboveground forest biomass dynamics with Landsat time-series and field inventory data: a comparison of empirical modeling approaches. *Remote Sens. Environ.* 114(5), 1053–1068 (2010).

34 Running SW, Nemani RR, Heinsch FA, Zhao MS, Reeves M, Hashimoto H. A continuous satellite-derived measure of global terrestrial primary production. *Bioscience* 54(6), 547–560 (2004).

35 Wang F, D'Sa EJ. Potential of MODIS EVI in identifying hurricane disturbance to coastal vegetation in the northern Gulf of Mexico. *Remote Sens.* 2, 1–18 (2010).

36 Sanchez-Azofeifa GA, Castro-Esau KL, Kurz WA, Joyce A. Monitoring carbon stocks in the tropics and the remote sensing operational limitations: from local to regional projects. *Ecol. Appl.* 19(2), 480–494 (2009).

37 Asner GP, Mascaro J, Muller-Landau HC *et al.* A universal airborne LiDAR approach for tropical forest carbon mapping. *Oecologia* 168(4), 1147–1160 (2011).

- **Overview of the potential role of airborne Light Detection and Ranging for mapping vegetation over large areas and estimating aboveground carbon stocks.**

38 Goetz S, Dubayah R. Advances in remote sensing technology and implications for measuring and monitoring forest carbon stocks and change. *Carbon Management* 2(3), 231–244 (2011).

39 Asner GP, Clark JK, Mascaro J *et al.* High-resolution mapping of forest carbon stocks in the Colombian Amazon. *Biogeosciences* 9(7), 2683–2696 (2012).

40 Hansen MC, Stehman SV, Potapov PV. Quantification of global gross forest cover loss. *Proc. Natl Acad. Sci. USA* 107(19), 8650–8655 (2010).

41 Hollinger DY. Defining a landscape-scale monitoring tier for the North American Carbon Program. In: *Field Measurements for Forest Carbon Monitoring: A Landscape-Scale Approach.* Hoover CM (Ed.). Springer, NY, USA (2010).

42 Baldocchi DD. Assessing the eddy covariance technique for evaluating carbon dioxide exchange rates of ecosystems: past, present and future. *Glob. Change Biol.* 9, 479–492 (2003).

43 Vargas R, Yepez E, Andrade JL *et al.* Progress and opportunities for water and greenhouse gases flux measurements in Mexican ecosystems: the MexFlux network. *Atmosfera* 26(3), 325–336 (2013).

44 Golinkoff JS, Running SW. A system to integrate multi-scaled data sources for improving terrestrial carbon balance estimates. In: *Land Use and the Carbon Cycle: Advances in Integrated Science, Management, and Policy.* Brown DG, Robinson DT, French NHF, Reed BC (Eds). Cambridge University Press, Cambridge, UK, 259–287 (2013).

- **Includes examples of some of the ways that intensive-site data can be used to reveal important characteristics of forest ecosystems that can help with measurement, reporting and verification implementation.**

45 Nave LE, Vance ED, Swanston CW, Curtis PS. Harvest impacts on soil carbon storage in temperate forests. *For. Ecol. Manage.* 259, 857–866 (2010).

46 Malhi Y, Luiz Eduardo OC, Metcalf DB *et al.* Comprehensive assessment of carbon productivity, allocation and storage in 3 Amazonian forests. *Glob. Change Biol.* 15(5), 1255–1274 (2009).

47 Gough CM, Vogel CS, Schmid HP, Curtis PS. Controls on annual forest carbon storage: lessons from the past and predictions for the future. *Bioscience* 58(7), 609–622 (2008).

48 Global Observations of Forest and Land Cover Dynamics. *A Sourcebook of Methods and Procedures for Monitoring and Reporting Anthropogenic Greenhouse Gas Emissions and Removals Caused by Deforestation, Gains and Losses of Carbon Stocks in Forests Remaining Forests, and Forestation.* Global Observations of Forest and Land Cover Dynamics Project Office, AB, Canada (2010).

49 Huntzinger DN, Post WM, Wei Y *et al.* North American Carbon Program (NACP) regional interim synthesis: terrestrial biospheric model intercomparison. *Ecol. Modell.* 232, 144–157 (2012).

50 Kurz WA, Dymond CC, White TM *et al.* CBM-CFS3: a model of carbon-dynamics in forestry and land-use change implementing IPCC standards. *Ecol. Modell.* 20(4), 480–504 (2009).

51 Lemay VM, Kurz AW. Estimating carbon stocks and stock changes in forests: linking models and data across scales. In: *Managing Forest Ecosystems: The Challenge of Climate Change.* Bravo F, Lemay V, Jandl R, Gadow KV (Eds). Springer, NY, USA, 63–81 (2008).

52 Wulder MA, White JC, Fournier RA *et al.* Spatially explicit large area biomass estimation: three approaches using forest inventory and remotely sensed imagery in a GIS. *Sensors* 8, 529–560 (2008)

53 IPCC. Use of models and facility-level data in greenhouse gas inventories. *Proceedings of the IPCC Expert Meeting on Use of Models and Measurements in Greenhouse Gas Inventories.* Sydney, NSW, Australia, 9–11 August 2010.

54 Liu SG, Bond-Lamberty B, Hicke JA *et al.* Simulating the impacts of disturbances on forest carbon cycling in North America: processes, data, models, and challenges. *J. Geophys. Res.* 116(G4), G00K08 (2011).

55 Ojima DS, Parton WJ, Schimel DS, Owensby CE. Simulated impacts of annual burning on prairie ecosystems. In: *Fire in North American Prairies.* Collins SL, Wallance L (Eds). University of Oklahoma Press, OK, USA (1990).

56 Landsberg JJ, Waring RH. A generalised model of forest productivity using simplified concepts of radiation-use efficiency, carbon balance and partitioning. *For. Ecol. Manage.* 95(3), 209–228 (1997).

57 Running SW, Coughlan JC. A general model of forest ecosystem processes for regional applications I. Hydrological balance, canopy gas exchange and primary production processes. *Ecol. Modell.* 42(2), 125–154 (1988).

58 Masera OR, Garza-Caligaris JF, Kanninen M *et al.* Modeling carbon sequestration in afforestation, agroforestry and forest management projects: the CO2FIX V.2 approach. *Ecol. Modell.* 164(2–3), 177–199 (2003).

59 Luo YK, Ogle C, Tucker S *et al.* Ecological forecasting and data assimilation in a data-rich Era. *Ecol. Appl.* 21, 1429–1442 (2011).

60 Li H, Wu J. Uncertainty analysis in ecological studies: an overview In: *Scaling and Uncertainty Analysis in Ecology: Methods and Applications.* Wu J, Jones K, Bruce L *et al.* (Eds). Springer, Dordrect, The Netherlands, 43–64 (2006).

61 Richards G, Evans D, Reddin A, Leitch J. *The FullCAM Carbon Accounting Model (Version 3.0) User Manual.* Department of Environment and Heritage, Canberra, ACT, Australia (2005).

62 Olguín M, Kurz W, De Jong B *et al.* Towards the use of the CBM-CFS3 model nationwide in Mexico: Chiapas pilot project. *Proceedings of the Third International Symposium on Carbon in Mexico.* Texcoco, Mexico, 21–24 May 2011.

63 Roswintiarti O. Indonesia's national carbon accounting system: overview, progress, and planning. *Proceedings of the Sixth Regional Workshop on Forest Monitoring. Technical America Initiatives GEO FCT ND.* San José, Costa Rica, 20–23 August 2012.

64 Kurz WA. Empirical and ecosystem models in higher-level tier reporting (lessons learned from Canada). *Proceedings of the Seventh Regional Workshop on Forest Monitoring. Technical America Inicitatives GEO FCT ND.* Merida, Mexico, 14–18 January 2013.

65 Parker C, Mitchell A, Trivedi M, Mardas N, Sosis K. *The Little REDD+ Book.* The Global Canopy Programme, Oxford, UK (2009).

66 Estrada M. *Standards and Methods Available for Estimating Project-Level REDD+ Carbon Benefits: Reference Guide for Project Developers.* Center for International Forestry Research, Bogor, Indonesia (2011).

67 Goward SN, Masek JG, Cohen W. Forest disturbance and North American carbon flux. *Eos* 89, 105–116 (2008).

68 Hansen MC, DeFries RS, Townshend JRG, Sohlberg R. Global land cover classification at 1 km spatial resolution using a classification tree approach. *Int. J. Remote Sens.* 21(6–7), 1331–1364 (2000).

69 Townshend JR, Masek JG, Huang C *et al.* Global characterization and monitoring of forestcover using Landsat data: opportunities and challenges. *Int. J. Digit. Earth* 5, 373–397 (2012).

70 Goetz SJ, Baccini A, Laporte NT *et al.* Mapping and monitoring carbon stocks with satellite observations: a comparison of methods. *Carbon Balance Manag.* 4, 2 (2009).

71 Baccini A, Laporte NT, Goetz SJ, Sun M, Dong H. A first map of tropical Africa's above-ground biomass derived from satellite imagery. *Environ. Res. Lett.* 045011 (2008).

72 Saatchi SS, Harris NL, Brown S *et al.* Benchmark map of forest carbon stocks in tropical regions across three continents. *Proc. Natl Acad. Sci. USA* 108(24), 9899–9904 (2011).

73 Cole J, Johnson K, Birdsey R *et al. Database for Landscape-Scale Carbon Monitoring Sites. General Technical Report NRS-xxx.* US Department of Agriculture, Forest Service, Northern Research Station, Newtown Square, PA, USA (2013) (In Press).

74 Eskelson BNI, Temesgen H, Lemay V *et al.* The roles of nearest neighbor methods in imputing missing data in forest inventory and monitoring databases. *Scand. J. For. Res.* 24, 235–246 (2009).

- **Very useful summary of imputation methods and their applications to forest mapping and assessments.**

75 Katila M, Tomppo E. Selecting estimation parameters for the Finnish multisource National Forest Inventory. *Remote Sens. Environ.* 76(1), 16–32 (2001).

76 Ohmann JL, Gregory MJ. Predictive mapping of forest composition and structure with direct gradient analysis and nearest-neighbor imputation in coastal Oregon, USA. *Can. J. For. Res.* 32(4), 725–741 (2002).

77 McRoberts RE, Tomppo EO, Finley AO, Heikkinen J. Estimating areal means and variances of forest attributes using the k-nearest neighbors technique and satellite imagery. *Remote Sens. Environ.* 111(4), 466–480 (2007).

78 Hudak AT, Crookston NL, Evans JS, Hall DE, Falkowski MJ. Nearest neighbor imputation of species-level, plot-scale forest structure attributes from LiDAR data. *Remote Sens. Environ.* 112(5), 2232–2245 (2008).

79 McRoberts RE, Tomppo EO, Næsset E. Advances and emerging issues in national forest inventories. *Scand. J. For. Res.* 25(4), 368–381 (2010).

80 Wilson BT, Woodall CW, Griffith DM. Imputing forest carbon stock estimates from inventory plots to a nationally continuous coverage. *Carbon Balance Manag.* 8, 1 (2013).

81 Riemann R, Wilson BT, Lister A, Parks S. An effective assessment protocol for continuous geospatial datasets of forest characteristics using USFS Forest Inventory and Analysis (FIA) data. *Remote Sens. Environ.* 114(10), 2337–2352 (2010).

82 Baffetta F, Fattorini L, Franceschi S, Corona P. Design-based approach to k-nearest neighbours technique for coupling field and remotely sensed data in forest surveys. *Remote Sens. Environ.* 113(3), 463–475 (2009).

83 Bernard F, Minang PA. *Strengthening Measurement, Reporting and Verification for REDD+.* International Institute for Sustainable Development, Winnipeg, Canada (2011).

84 Gibbs HK, Brown S, Niles JO, Foley JA. Monitoring and estimating tropical forest carbon stocks: making REDD a reality. *Environ. Res. Lett.* 2(4), 045023 (2007).

85 White D, Minang PA. *Estimating the Opportunity Costs of REDD+: A Training Manual, Version 1.3.* UN-REDD Programme, Geneva, Switzerland (2011).

86 IPCC. *Good Practice Guidance and Uncertainty Management in National Greenhouse Gas Inventories.* Institute for Global Environmental Strategies, Hayana, Japan (2000).

87 Grassi G, Monni S, Federici S, Achard F, Mollicone D. Applying the conservativeness principle to REDD to deal with the uncertainties of the estimates. *Environ. Res. Lett.* 3, 035005 (2008).

88 Wu J, Li H. Uncertainty analysis in ecological studies: an overview. In: *Scaling and Uncertainty Analysis in Ecology.* Wu J, Jones KB, Li H, Loucks OL (Eds). Springer, Dordrecht, The Netherlands, 45–66 (2006).

89 Lehrter JC, Cebrian J. Uncertainty propagation in an ecosystem nutrient budget. *Ecol. Appl.* 20(2), 508–524 (2010).

90 Yanai RD, Battles JJ, Richardson AD *et al.* Estimating uncertainty in ecosystem budget calculations. *Ecosystems* 13(2), 239–248 (2010).

91 Jansen MJW. Prediction error through modelling concepts and uncertainty from basic data. *Nutr. Cycl. Agroecosys.* 50(1–3), 247–253 (1998).

92 Katz RW. Techniques for estimating uncertainty in climate change scenarios and impact studies. *Climate Res.* 20(2), 167–185 (2002).

93 Group on Earth Observation-Forest Carbon Tracking Task. *Proceedings of the Seventh Regional Workshop on Forest Monitoring Technical America Initiatives GEO-FCT.* Mérida, Mexico, 14–18 January 2013.

94 Pappenberger F, Beven KJ. Ignorance is bliss: or seven reasons not to use uncertainty analysis. *Water Resour. Res.* 42(5), W05302 (2006).

95 Watt P, Watt M. Applying satellite imagery for forest planning. *NZ J. For.* 56(1), 23–25 (2011).

96 Walker WS, Stickler CM, Kellndorfer JM *et al.* Large-area classification and mapping of forest and land cover in the Brazilian Amazon: a comparative analysis of ALOS/PALSAR and Landsat data sources. *IEEE J. Sel. Top. Appl. Earth Observ. Remote Sens.* 3, 594–604 (2010).

97 Jusoff K. Precision forestry using airborne hyperspectral imaging sensor. *J. Agr. Sci.* 1(1) 142–147 (2009).

98 Phillips OL, Higuchi N, Vieira S, Baker TR, Chao KJ, Lewis SL. Changes in Amazonian forest biomass, dynamics, and composition, 1980–2002. *Geophys. Monogr. Ser.* 186, 373–387 (2009).

99 Marthews TR, Metcalfe D, Malhi Y *et al.* *Measuring Tropical Forest Carbon Allocation and Cycling: A RAINFOR-GEM Field Manual for Intensive Census Plots (v2.2).* Global Ecosystems Monitoring Network, Oxford, UK (2012).

100 Blackard JA, Finco MV, Helmer EH *et al.* Mapping US forest biomass using nationwide forest inventory data and moderate resolution information. *Remote Sens. Environ.* 112(4), 1658–1677 (2008).

101 Miao Z, Lathrop R, Xu M *et al.* Simulation and sensitivity analysis of carbon storage and fluxes in the New Jersey Pinelands. *Environ. Model. Softw.* 26(9), 1112–1122 (2011)

102 Turner, DP, WD Ritts, BE Law *et al.* Scaling net ecosystem production and net biome production over a heterogeneous region in the western United States. *Biogeosciences* 4, 597–612 (2007).

103 Cramer W, Bondeau A, Woodward FI *et al.* Global response of terrestrial ecosystem structure and function to CO_2 and climate change: results from six dynamic global vegetation models. *Glob. Change Biol.* 7(4), 357–373 (2001).

104 Sitch S, Huntingford C, Gedney N *et al.* Evaluation of the terrestrial carbon cycle, future plant geography and climate-carbon cycle feedbacks using five Dynamic Global Vegetation Models (DGVMs). *Glob. Change Biol.* 14(9), 2015–2039 (2008).

105 Purves DW, Lichstein JW, Strigul N, Pacala SW. Predicting and understanding forest dynamics using a simple tractable model. *Proc. Natl Acad. Sci. USA* 105, 17018–17022 (2008).

106 Lewis SL, Lloyd J, Sitch S, Mitchard ETA, Laurance WF. Changing ecology of tropical forests: evidence and drivers. *Annu. Rev. Ecol. Evol.* S40, 529–549 (2009).

107 Van Oijen M, Rougier J, Smith R. Bayesian calibration of process-based forest models: bridging the gap between models and data. *Tree Physiol.* 25(7), 915–927 (2005).

108 Van Oijen M, Thomson A. Toward Bayesian uncertainty quantification for forestry models used in the United Kingdom Greenhouse Gas Inventory for land use, land use change, and forestry. *Clim. Change* 103(1–2), 55–67 (2010).

Websites

201 UNFCCC. Reducing emissions from deforestation in developing countries: approaches to stimulate action. Submissions from Parties. http://unfccc.int/documentation/documents/advanced_search/items/6911.php?priref=600003611#beg

202 UNFCCC. National Reports. Contents and timetable. http://unfccc.int/national_reports/items/1408.php

203 SilvaCarbon. http://silvacarbon.com

204 IPCC Task Force on National Greenhouse Gas Inventories. www.ipcc-nggip.iges.or.jp

205 The Climate Registry. http://theclimateregistry.org

206 Global Observation of Forest and Land Cover Dynamics. http://fao.org/gtos/gofc-gold/index.html

207 The Global Forest Observations Initiative. www.gfoi.org

208 Glob Allome Tree. www.globallometree.org

209 Kellndorfer J, Walker W, Lapoint E *et al.* North American Carbon Program Aboveground Biomass and Carbon Baseline Data. http://daac.ornl.gov/cgi-bin/dsviewer.pl?ds_id=1161

210 Report of workshop on moving from lower to higher tiers of estimating and reporting greenhouse gas emissions and sinks for forests, Merida, Mexico. https://sites.google.com/site/talleresgeofct/sptimo-taller-regional-geo-fct-de-monitoreo-de-bosques