Chapter 7

Methods of Measuring Carbon in Forests

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EXECUTIVE SUMMARY

Accurate measurement of carbon stocks and flux in forests is one of the most important scientific bases for successful climate and carbon policy implementation. A measurement framework for monitoring carbon storage and emissions from forests should provide the core tool to qualify country and project level commitments under the United Nations Framework Convention on Climate Change, and to monitor the implementation of the Kyoto Protocol.

Currently, there are several methods for estimating forest carbon stocks and flux, ranging from the relatively simple forest biomass inventory to complex, sophisticated experiments and models. Advanced carbon estimation methodologies such as LiDAR and eddy covariance carbon flux experiments may provide reliable, accurate and transparent data and serve as a basis for market tools and international policymaking such as carbon trading, carbon taxes, and credits for reducing emissions from deforestation and forest degradation in developing countries (REDD, REDD+). Nevertheless, developing countries, which have limited capacity for data collection and management, need low-cost methodologies with acceptable spatial and temporal resolution and appropriate sampling intensity.

If a standardized verification system across projects, countries, and regions is to ever be attained, policymakers should be aware that there are different basic approaches to measuring forest carbon, which have advantages and disadvantages, and varying degrees of accuracy and precision.

We review the four categories of methods for measuring forest biomass and estimating carbon which are currently in use: i) forest inventory (biomass); ii) remote sensing (relationship between biomass and land cover); iii) eddy covariance (direct
measurement of CO₂ release and uptake); and iv) the inverse method (relationship among biomass, CO₂ flux and CO₂ atmospheric transport). These methods all vary in their level of accuracy and the resolution at which data can be obtained. Each technique has its own advantages and disadvantages and there are appropriate circumstances for using each one in measuring CO₂ flux and carbon storage for different temporal and spatial scales of evaluation and measurement.

Forest inventory methods are direct measures of biomass accumulation within a forest.

They have a long history in development and good data is generally available; however, they are low in time resolution, costly to implement, require technical training and knowledge, are variable in standards for measurement, and are available in only certain regions, mostly developed countries.

Remote sensing methods usually are combined with models that link remote sensing information with CO₂ and carbon data (often forest inventory information). Methods can be divided into passive sensing (satellite images, aerial photographs that are characterized by reflected light) and active sensing (radar, LiDAR that emit and receive microwaves or light respectively). Remote sensing is limited by incomplete information, resolution and detection problems, and uncertainties in models that require further development and refinement. Nevertheless, when available at a suitable resolution and spatial scale, it can be the cheapest method of surveying forests.

The eddy covariance method is advanced in its accuracy and resolution, and is a good method for direct measurement of small (hectare-plus) scale CO₂ flux; but, it is still restricted by systematic biases, is not accurate in rough topography, and has limited observation sites around the world.

Inverse methods typically are used at continental or global scales. These methods calculate the total sources and sinks, including both anthropogenic and natural, using available atmospheric CO₂ concentration data and transportation models. Carbon Tracker is one of the most advanced inverse methods. It was developed by NOAA’s Earth Systems Research Laboratory as a system to keep track of carbon dioxide uptake and release at the Earth’s surface over time and to continuously improve models and data assimilation methods for higher accuracy and resolution.

What we do and do not know about measuring carbon in forests

- Forest inventory methods require historical and regional data. Permanent continuous forest inventory (CFI) plots are the best to provide long-term accurate and non-biased assessments. Non-permanent plots can be used but are often biased.

- Most developed countries conduct regular national inventories to evaluate forest health and status. These inventories are therefore a useful data base if biases can be avoided.

- In the past, inventory plots have often been biased toward sampling forests of commercial value. Forests considered degraded or that are now growing back (secondary forest) are often under-represented. Inventories often only
include tree species that have commercial value and under-sample small trees.

- Very few inventories account for belowground biomass, litter, and dead wood. Fine spatial-resolution (1-10 m) satellite data have the advantage in providing high resolution details of a specific area. However, disadvantages include a small area of coverage, shadows, and expense in acquisition.

- It is expensive to sample a sufficient number of trees representing the diversity of size and species to generate local allometric equations for use in converting tree data to forest biomass data.

- Medium spatial-resolution (10-100 m) satellite data are the most suitable for regional level above-ground biomass estimation because of better data availability (spatial and temporal), and the lower cost of acquisition and storage. Since spatial resolution is usually sufficient to compare with inventory measurements, this approach is widely used for forests.

- Coarse spatial resolution satellite data (> 100 m) are most effective at large national or continental scales. The use at such scales is limited, however, because of the occurrence of mixed pixels, and differences between scale and resolution of forest inventory measurements.

- Aboveground biomass estimation by radar can achieve good accuracy in low and medium density forests, but the relationship between radar backscatter and aboveground biomass weakens when the forest becomes too dense. Its advantage is its ability to penetrate precipitation and cloud cover, and avoid shade/shadow effects from the sun.

- Light Detection and Ranging (LiDAR) is an active remote sensing method, analogous to radar, but using laser light instead of microwaves. The technology needs further development to be widely useful in aboveground biomass estimation.

- Recent technical, financial and logistical (scheduling) problems with the U.S. remote sensing program highlight the need for more countries or consortiums to provide the international remote sensing community with more options in satellite imagery and Radar/LiDAR data.

- Eddy covariance measurements have been continuously made at certain sites for over ten years. New observation sites (especially in tropical forest regions), updated models, and remote sensing data will enable eddy covariance methods to continually refine estimates of CO₂ flux from regional to continental scales, making eddy covariance the world’s direct tracking system of carbon flux.

- More research needs to be conducted to close the energy budget in eddy covariance measurements and eliminate biases caused by nighttime stratification and complex topography.
CarbonTracker has emerged as one of the most advanced inverse models currently used for regional and continental inverse estimates of carbon sinks and sources.

**Keywords:** biometrics, carbon flux, Carbon Tracker, climate change, eddy covariance, forest inventory, global observation network, inverse methods, remote sensing, sequestration

**INTRODUCTION**

The need to accurately measure the stocks and flux of carbon in forests is urgent given the global consensus that CO₂ emissions have a very strong influence on global warming. Forests are an essential part of the carbon cycle. They are a major terrestrial sink of CO₂, but their land use conversion to agriculture currently accounts for 25% of global carbon emissions. Compared to the combustion of fossil fuel, emissions from land use change are an important issue for developing countries and especially for tropical countries (Houghton and Ramakrishna, 1999). Forests are influenced by various anthropogenic and natural disturbances such as fire, disease, insect infestations, harvesting, deforestation, and degradation, all of which can lead to significant carbon emissions. To understand the carbon cycle in the forest, it is important to have valid, cost-effective scientific methods to measure and monitor carbon. Such measures require accuracy and precision in order to have useful data on carbon stocks and flux in forests globally.

Accurate estimation of forest carbon stocks and flux in is one of the most important scientific bases for successful policy implementation. Although understanding the methods of measuring the forest carbon cycle may not be a focus of policymakers, it is important that they recognize that there are differences between regions and countries in carbon emission behaviors and carbon storage in forests (and associated land conversion). This understanding will allow them to make better decisions about global and regional resource allocation for measurement capacity, and therefore to optimize adaptation and mitigation strategies for climate change. A measurement framework for monitoring carbon storage and emissions from forests should be the core tool to qualify country and project level commitments under the United Nations Framework Convention on Climate Change (UNFCCC, 1997), and to monitor the implementation of the Kyoto Protocol (Brown, 2002).

To meet the requirements of the Kyoto Protocol, all Annex I countries must “provide data to establish their level of carbon stocks in 1990 and to enable an estimation of its changes in carbon stocks in subsequent years” (UNFCCC, 1997). Developing countries, which have limited capacity in data collection and management, need methodologies with low-cost, acceptable spatial and temporal resolution and appropriate sampling intensity. Furthermore, for the post-Kyoto era, advanced carbon estimation methodologies may provide reliable, accurate, and transparent data and serve as a basis for market tools and international policymaking.

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1 Annex I Parties to the United Nations Framework Convention on Climate Change (UNFCCC) include the industrialized countries that were members of the OECD (Organisation for Economic Co-operation and Development) in 1992, plus countries with economies in transition (the EIT Parties), including the Russian Federation, the Baltic States, and several Central and Eastern European States.
such as carbon trading, carbon taxes, and credits for reducing emissions from
deforestation and forest degradation in developing countries (REDD, REDD+).

**Objectives**

In this chapter we describe four basic methods of measuring carbon storage and flux
in forests: i) forest inventory; ii) remote sensing; iii) eddy covariance; and iv) the
inverse method. These methods are critiqued for their advantages and disadvantages
in estimating CO₂ flux and storage. All are evaluated for their accuracy and
resolution. In the conclusion section, we describe gaps in data, information, and
technologies that need to be addressed if a standardized measurement framework is
to be achieved. Recommendations are made on improvements in methodology for
more efficient and effective aboveground biomass (AGB) estimation.

**Measuring carbon**

Generally, there are two main approaches to measuring carbon stocks and fluxes in
each forest carbon pool: (i) measuring changes in carbon stock, and then inferring a
carbon flux under a certain level of confidence; and (ii) measuring carbon flux
directly. Generally, biomass, which is readily measured, is widely used to estimate
carbon stocks using proven formulas for the ratio of carbon to biomass instead of
measuring carbon directly, particularly for aboveground carbon (Brown, 1997).

Carbon stocks in forests can be classified into five different measurement pools:

- **Aboveground biomass** – Living biomass above the soil, including stem,
stump, branches, bark, seeds, and foliage. This category includes live
understory.

- **Belowground biomass** – All living biomass of roots greater than a certain
diameter.

- **Dead wood** – Includes all non-living woody biomass either standing, lying
on the ground (but not including litter), or in the soil.

- **Litter** – Includes the litter, humus layers of the soil surface, and all non-living
biomass of a certain diameter lying on the ground.

- **Soil organic carbon (SOC)** – Typically includes all organic material in soil to a
depth of 1 meter, excluding the coarse roots of the belowground biomass pool.

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**FOREST INVENTORIES AND ABOVEGROUND CARBON STOCK ESTIMATIONS**

Because national forest inventories are commonly available for many countries,
different approaches have been developed to estimate above ground biomass (AGB)
from inventories. They can be categorized by data source: (i) field measurement; (ii)
remote-sensing data; or (iii) ancillary data used in GIS-based modeling (Lu, 2006;
Wulder et al., 2008). Several approaches to estimating carbon stocks from each of
these data sources are shown in Table 1.
Table 1 Summary of techniques for above ground carbon stock estimation

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<td>Anderson et al., 2006; Drake et al., 2003; Lefsky et al., 1999</td>
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Source: Modified from Lu (2006)

**Field-based methods**

The field-based method is usually referred to as an inventory assessment, and can be further classified into volume-to-biomass and diameter-to-biomass approaches. The choice between these approaches is dependent upon the data available and the desired resolution. Generally, the approach of converting timber volume, which is commonly
available, to biomass has more uncertainty but requires less detailed data; therefore, this is the most commonly used method. If detailed diameter information and field measurements are available for establishing allometric equations, then the diameter-to-biomass (allometric) approach is generally favored because it is more accurate.

Timber volume data are available for many countries because these data are primarily collected for forest management and revenue accounting. In 1919 (Norway), 1921-24 (Finland), and 1923-24 (Sweden), the Nordic nations started national forest inventories because of the fear that the fuelwood resource would be exhausted (FAO, 2000; Brack, 2009). Optimally, species, diameter at breast height (DBH), height, site quality, age, increment, and defects are recorded in each inventory dataset (LeBlanc, 2009). However, different countries have various capacities and standards for detailing the inventory information. For example, Forest Statistics of China 1984-1988 is compiled from more than 250,000 permanent and temporary plots across China, and the technical standard in data collection includes measuring DBH, height, stem volume, age, total area, and site quality (Fang et al., 1998). But in the National Forest Inventory of Indonesia 1989-1996, only the number of trees per ha and volume per ha for different diameter classes is available (FAO, 2000). In Brazil, very limited data collection is done regionally by consultants, but not by the government or the research academy (Freitas, 2006; Wardoyo, 2008). It is therefore necessary for some countries to utilize available timber volume data from private company and landowner inventories so as to obtain rudimentary baseline domestic estimates of changes and stocks of standing forest carbon.

**Estimating biomass from timber volume**

The biomass expansion factor (BEF) is defined as the ratio of all standing aboveground biomass (AGB) to growing stock volume (Mg/m³) (Fang et al., 2001). It has been developed to estimate aboveground biomass when timber volumes within diameter classes are reported (Brown, 2002). Especially for estimating large areas within developing countries that lack detailed information about forest biomass, the BEF is a practical estimate of AGB.

The process of estimating carbon stock by BEF can be simply to use the regression relationships between merchantable plot tree volumes, their annual increments, and estimates of non merchantable volumes, to above ground standing biomass. Estimations of total aboveground biomass from tree volume data is then subsequently expanded to an area based on uniformity of site, stocking and age-class distribution (see Figure 1 for example) (Wulder et al., 2008). BEF varies by different stand density-related factors, such as forest age, site class, stand density, and other biotic and abiotic factors (Brown et al., 1999; Fang et al., 2001). The largest differences are regional and by forest type (see Figure 2) (Brown, 2002).

**Estimating biomass from tree diameter**

Compared to the BEF method, allometric equations can provide more precise estimates of aboveground biomass. In the biological sciences, the study of the
relationship between the size and shape of organisms is called allometry (Niklas, 1994). In the context of biomass estimation, allometry refers to the relationship between individual tree diameters (sometimes with heights) and aboveground biomass for specific species, groups of species, or growth form (Jenkins et al., 2003; Zianis and Mencuccini, 2004).

Figure 1 An overview of the process used to estimated biomass from the forest inventory data


In order to derive an accurate allometric equation for any forest type, an adequate sample of tree sizes and species must be taken. If such data are available at the appropriate scale, the allometric approach can be very accurate. Generally, species groups such as tropical wet-evergreen hardwoods, temperate eastern U.S. hardwoods, pines, and spruces produce highly significant correlations of greater than 0.98 for regressions between diameter at breast height (dbh) and biomass per tree (Brown, 1997, Schroeder et al., 1997; Brown et al., 1999; Brown, 2002). A study on in lianas in Amazon semi-evergreen rain forest showed that a combination of diameter and length is also significantly correlated with biomass (R² =0.91) (Gehring et al., 2004). This approach is limited, however, by the lack of allometric data for many forest types and regions.
Figure 2  Relationship between BEF for temperate hardwoods, pines and spruce, and tropical hardwoods


*Improvement for field based methods*

Estimates of carbon flux from forest inventory measurements require availability of historical data at the regional scale. All developed countries conduct regular national inventories (FAO, 2000). For the 137 developing countries, 22 have repeated inventories, 54 have a single inventory, 33 have partial forest inventories, and 28 countries have no inventory (Holmgren and Persson, 2002). In the U.S., a vast network of permanent sample plots makes up the Forest Inventory and Analysis (FIA) and Forest Health Monitoring (FHM) programs. The FIA program, which has been operating for about 70 years, periodically measures all plots on a state-by-state basis every 5-14 years (Brown, 2002; Smith et al., 2002).

Inventory data have several deficiencies that can bring uncertainty, however. First, inventories tend to be conducted in forests that are considered to have commercial value, and the forests that many people depend upon for other values (such as water, recreation, open space, or subsistence) may not be included. Many degraded or semi-deforested open lands, or those regions that are now growing back (secondary forest) are under-sampled or not measured. Often only trees species that have commercial value at the time of the inventory are counted (Brown, 1997). This counting bias can bring systematic inaccuracy to the estimation of carbon. Additionally, the assumption that small trees (about 10 cm diameter or less) contribute little to the total forest biomass is not robust according to Schroeder et al. (1997). They concluded that for young hardwood stands in the eastern USA with aboveground biomass less than 50 Mg/ha, trees with dbh of 10 cm or less contain as much as 75% of the biomass of trees with dbh greater than 10 cm.
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The cost is high to sample a sufficient number of trees representing a range of size and species in order to generate local allometric equations (Brown, 2002). Many developing countries lack funding, staff, and expertise to acquire the data. Additionally, a small number of large diameter trees (>100 cm) and a large number of small diameter trees (<10 cm), which are important to the total biomass, are often missed in a sample for allometry measurements (Brown, 1997).

To improve the accuracy and precision of measuring aboveground live tree biomass by inventory methods, Brown (2002) has suggested that the following:

- Destructively harvest large diameter trees to establish allometry equations, because they are under-sampled and they have a significant influence on the regression relationship between diameter and biomass.
- Precisely measure small trees (10 cm diameter or less) for temperate hardwood forests (i.e. second growth) or other forest types in which small diameter trees may be significantly underestimated.
- Including height in regression equations can slightly improve the precision, but given the difficulty of measurement, it is not feasible or worth the effort for large areas. The use of remote sensing data can complement tree height data for large-areas, and can improve the precision of allometric regression equations.
- Periodically re-visit the field sites from which the inventory data are derived and modify the allometric equations that may have changed with time and forest growth.

REMOTE SENSING METHODS

Inventory data have been used as the basic approach to estimating carbon stock in existing and historical forests worldwide. In recent years, better models and the establishment of more plots have improved accuracy and precision (Smith and Heath, 2004). However, sampling intervals are long (5-14 years), so temporal resolution of changes in carbon storage is limited. In addition, gathering inventory data is highly dependent on the capacity of local people to conduct the survey. Assuming that land use change accounts for a significant part of carbon emissions, and that the rate of deforestation is high, remote sensing would appear to be a more suitable method, particularly for use in large and remote forest regions and in developing countries where training on forest inventory procedures is poor.

The remote sensing method monitors forests at different temporal, spatial and spectral resolutions (Patenaude et al., 2005). Several applications of remote sensing for mapping land covers are available and can be categorized as passive (optical) or active (radar).

Optical, or passive, remote sensing technologies include aerial photographs of various kinds (infrared, color, black and white), Normalized Difference Vegetation Index (NDVI) images that are derived from an advanced very high resolution radiometer (AVHRR) sensor, and images from Landsat Thematic Mapper (TM) false
color composites and its associates that are at a low resolution (Figure 3). Active remote sensing technologies include radar and LiDAR derived images. These can measure structure, detect objects below canopy, and can depict canopy height and stratification (CHM) (Figure 3).

Figure 3 Example of different remote sensing methods on the same site.


Optical remote sensing

Optical remote sensing captures solar energy reflected by the forest canopy in the visible, near, and middle infrared portion (0.4 to 2.5 mm) (Patenaude et al., 2005). Optical remote sensing is also called passive remote sensing and can be differentiated from Radar and LiDAR methods, which actively emit radiation and then detect the reflectance. The ground sampling distance (GSD) defines the spatial resolution level of the optical remote sensing methods. It can be classified based on degree of resolution into fine, medium, and coarse spatial scales.
**Fine spatial-resolution data**

Fine spatial-resolution data has a GSD less than 10 m. Aerial photographs (GSD 1.00 m), IKONOS (GSD 0.83 m), and QuickBird (GSD 0.61 m) images are the commonly available fine spatial-resolution data (Lu, 2006).

Aerial photographs were widely used in forest surveys starting in the late 1940s, primarily for forest type delineation and stratification, and timber volume estimation (Lu, 2006). Since the 1990s, space-borne high spatial-resolution satellite images can also be used in biomass estimation as well as in detecting biophysical parameters (height, classification, stand structure). Such images can be used to detect the structural diversity of a forest at a small scale. For example, the IKONOS system, started in September 1999, collects panchromatic data, with a spectral range of 450 to 900 nm, and four GSD channels of 4 m resolution multi-spectral data (Wulder et al., 2004). Thenkabail et al. (2004b) used multi-date wet and dry season IKONOS images to calculate carbon stock levels of the West African oil palm plantations. It was also used by Thenkabail (2003) to detect small differences in floristic association in the Central African rainforest.

Fine spatial-resolution remote sensing data has the advantage in providing details of a specific area. However, disadvantages include the small area of coverage, preponderance of shadows, and acquisition expense. Therefore, it should mainly be used in small scale projects that are focused on measuring stand-level characteristics (Thenkabail et al., 2004b). Such fine scale resolution can also be useful for the development of reference data for validation or accuracy assessments of medium and coarse scale remote sensing measurements (Lu, 2006).

**Medium spatial-resolution data**

Medium spatial-resolution remote sensing images (10 m to 100 m) are the most suitable for regional level aboveground biomass estimation because of better data availability (spatial and temporal), and the lower cost of acquisition and storage. Since spatial resolution is still good enough to compare with inventory measurements, this approach is widely used for aboveground biomass estimation for various forests (Reese et al., 2002; Tomppo et al., 2002; Foody et al., 2003; Zheng et al., 2004; Muukkonen and Heiskanen, 2005, 2007). Landsat Thematic Mapper (TM), Enhanced Thematic Mapper Plus (ETM+), Multi-Spectral Sensor (MSS), ASTER, AVIRS, and SPOT High Resolution Visible (HRV) are all multispectral sensors commonly used for mapping forest structure and estimating biomass (Muukkonen and Heiskanen, 2005).

Landsat has been the most important data source for mapping and remote sensing interpretation. For more than 30 years it has provided appropriate spatial and spectral resolution to detect and characterize forests at an affordable cost (Cohen and Goward, 2004). Since 1972, the Landsat program has launched seven satellites. With each launch, sensors have been designed for better spatial and spectral resolution. Landsats 1, 2, 3, and 4 have been decommissioned because better satellites are now available or they had reached the end of their working life. However, due to the failure
of Landsat 6 and a defective scan line on Landsat 7, Landsat 5 has been kept running for 24 years and is still widely used for research. The earliest sensor (four-band multispectral scanner sensor – MSS) was deployed on Landsat satellites 1 to 5. But because of the lower spatial resolution (80 m), and fewer spectral bands of MSS, the TM instrument, and then later the ETM+ instrument, which have seven spectral bands and 30 m spatial resolution, are now the primary images used in aboveground biomass estimation (Figure 4).

Figure 4  Aboveground biomass of secondary forest versus TM channel 5 reflectance.


The Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) was launched in 1999, with three spectral bands in the visible near-infrared region (VNIR), six bands in the shortwave infrared region (SWIR), and five bands in the thermal infrared region (TIR), with 15-, 30-, and 90-m spatial resolution, respectively (Muukkonen and Heiskanen, 2005). In spite of its modernity, it is argued that ASTER has relatively narrow SWIR bands 5-8 which are primarily designed for soil and mineral detection, so it is not particularly sensitive to detecting differences among forests (Yamaguchi et al., 1998).

Coarse spatial-resolution data

Overall, coarse spatial-resolution data (greater than 100 m) are most effective at large national or continental scales. However, use at such scales is limited because of the frequent occurrence of mixed-landuse pixels (due to the large pixel size), and differences between scale and resolution of forest inventory measurements and image GSD (Lu, 2006). However, the use of fine and medium spatial-resolution data along with coarse spatial-resolution can help estimate aboveground biomass and improve accuracy (Dong et al., 2003; Muukkonen and Heiskanen, 2007; Zheng et al., 2007a).

Commonly used coarse spatial-resolution data include NOAA Advanced Very High Resolution Radiometer (AVHRR), Moderate Resolution Imaging Spectroradiometer (MODIS), and SPOT VEGETATION (Table 2) (Lu, 2006). The AVHRR
has collected over 30 years of data and has often been used to assess large areas of forest cover at the scale of a continent (Iverson et al., 1994). For example, for a 1.42 billion ha region of temperate and boreal forest, Dong et al. (2003) used regression analysis between an NDVI dataset, developed from AVHRR at 8x8 km resolution, over an eighteen year period (1981-1999), and timber volumes from forest inventories to estimate aboveground biomass.

Table 2  Selected examples of biomass estimation using optical remote sensing data

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<td>Landsat TM and IRS-1C WiFS</td>
<td>Finland and Sweden</td>
<td>K nearest-neighbor method and nonlinear regression</td>
<td>Tomppo et al., 2002</td>
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Source: modified from Lu (2006).

The recent SPOT VEGETATION (VGT) sensor provides imagery with a swath width of 2,250 km and GSD at 1,165 m. Besides the four spectral bands of the SPOT multi-spectral sensor, the Vegetation Instrument has an extra band (0.43 to 0.47 µm) that is used for the first band (blue) and a 1.65-µm short-wave infrared (SWIR) channel. Fraser and Li (2002) tested the relationship between several values and indexes from VGT and aboveground biomass. The short-wave-based vegetation index (SWVI), in which the SWIR is substituted for the red channels from VGT, has been found to have weak correlation (R²=0.25). The other values (red, NIR, SWIR, and NDVII) have either no relation or poor relation with aboveground biomass, and therefore are not useful.

MODIS is a 36-band spectrometer providing a global dataset every 1-2 days with a 16-day repeat cycle. Bands 1 and 2 have GSD at 250 m, bands 3-7 have GSD at 500 m, and bands 8-36 have GSD at 1,000 m. Zheng et al. (2007a) used Landsat 7 ETM+ data and field observations to develop an empirical model.
calibration with different sensors, MODIS data were used for model applications at a regional scale. Using a similar approach, Muukkonen and Heiskanen (2007) used ASTER (15×15 m) data to develop regression models with stand forest inventory data volume. MODIS bands 1 and 2 (250×250 m) data were used to estimate stand volume.

*Interpretation of optical remote sensing data*

Specific interpretation procedures have been developed to extract information from images. Generally, the procedures are divided into two classes: the traditional approach using parametric methods such as regression models (Holmgren et al., 1997; Steininger, 2000), and nonparametric methods such as the k-nearest-neighbor method (k-NN) (Fazakas et al., 1999; Reese et al., 2002) (Table 2).

Since coarse spatial resolution data are difficult to couple with forest inventory measurements, researchers usually use fine or medium spatial scale resolution data to link forest inventory data to coarse spatial resolution regional data (Muukkonen and Heiskanen, 2007).

Regression models differ in variables and equations. Spectral signatures, image textures, and vegetation indexes are among the variables derived from imagery. For example, Lu and Batistella (2005) found that in the Amazon, successional forest is more likely to correlate with a spectral signature, and mature forest is more likely to correlate with texture. Zheng et al. (2007b) showed that leaf area index (LAI), and the normalized difference vegetation index (NDVI) are significant predictors for Chinese fir aboveground biomass, while LAI and stand age can predict 94% of the variation of aboveground biomass.

Regression models include linear, non-linear, multi-, and neural networks. Neural networks in forestry mainly deal with incomplete, disturbed, and noisy datasets (Hanewinkel, 2005). The neural network model was used by Steininger (2000) to develop predictive models of biomass (for example, see Figure 4). Foody et al. (2003) used multiple regression and neural networks to estimate tropical forest biomass and observed a significant relationship between predicted biomass and that measured from the forest inventories. Other researchers either use ASTER data to estimate aboveground biomass, applying non-linear regression analysis and a neural network approach (Muukkonen and Heiskanen, 2005), or fractional textures and semivariance analysis of image fractions integrated with conventional images to establish stepwise multiple regression models to predict forest structure and health (Levesque and King, 2003).

Recently, nonparametric methods such as the k-nearest-neighbor method (k-NN) and k most similar neighbor method (k-MSN) have been used to interpret images. In these methods, the prediction is no longer dependent upon the regression of the whole sample space, but on either the weighted mean of neighbors or the distance-weighted mean of most similar neighbors. The accuracy of AGB estimation was tested using the k-MSN method and was deemed acceptable (Anttila, 2002). In Sweden, Landsat data was successfully combined with the k-NN method to estimate AGB (Fazakas et al., 1999; Reese et al., 2002).
Active remote sensing: Radar and LiDAR

Unlike optical remote sensing methods using aerial photographs and satellite images that capture the reflectance of solar radiation, Radar and LiDAR systems use their own electromagnetic radiation source independent of solar radiation. Moreover, the microwave portion of the radar wavelength can penetrate precipitation and cloud cover, and avoid shade/shadow effects from the sun (Ranson and Sun, 1994; Patenaude et al., 2005). In addition LiDAR can capture detailed stand structure and height, something difficult to achieve by the optical remote sensing method (see Table 3 for examples).

Table 3  Selected examples of biomass estimation using radar and LiDAR data

<table>
<thead>
<tr>
<th>Datasets</th>
<th>Study area</th>
<th>Techniques</th>
<th>References</th>
</tr>
</thead>
<tbody>
<tr>
<td>SIR-C</td>
<td>South-eastern USA</td>
<td>Multiple regression analysis</td>
<td>Harrell et al., 1997</td>
</tr>
<tr>
<td>SIR-C</td>
<td>Siberia</td>
<td>Adapted theoretical regression model</td>
<td>Sun et al., 2002</td>
</tr>
<tr>
<td>JERS-1 SAR L-band</td>
<td>Ta’pajos, Para’ state and Manaus, Amazonas state, Brazil</td>
<td>Forest backscatter regression model</td>
<td>Luckman et al., 1998</td>
</tr>
<tr>
<td>JERS-1 SAR L-band</td>
<td>New South Wales, Australia</td>
<td>Linear regression analysis</td>
<td>Austin et al., 2003</td>
</tr>
<tr>
<td>Airborne laser</td>
<td>Costa Rica</td>
<td>Linear regression, canopy height models</td>
<td>Nelson et al., 1997</td>
</tr>
<tr>
<td>Large-footprint LiDAR</td>
<td>North-east Costa Rica</td>
<td>Multiple regression analysis</td>
<td>Drake et al., 2003</td>
</tr>
<tr>
<td>Small-footprint LiDAR</td>
<td>Piedmont physiographic province of Virginia, south-eastern USA</td>
<td>Measure crown diameter using LiDAR, then estimate biomass using regression analysis</td>
<td>Popescu et al., 2003</td>
</tr>
</tbody>
</table>

Source: modified from Lu (2006).

Radar data

Radio Detection and Ranging (RADAR) systems work by virtue of radiating microwave pulses to subjects and then measuring the returned echo’s amplitude (backscatter amplitude) and orientation (polarization). The wavelength emitted in radar is between approximately 1 mm and 1 m. In this range, the C (3.75-7.5 cm), L (15-30 cm), and P (30-100 cm) bands are responsive, respectively, to small structural components (e.g. leaves), large components (e.g. branches), and larger components (e.g. trunks) (Patenaude et al., 2005). Unlike optical remote sensing that detects differences in reflectance of various vegetation and mineral surfaces, radar remotely detects the surface roughness, geometry, and water content of biomass.

There are two types of imaging radar, the earlier Side-Looking Airborne Radar (SLAR) and the later Synthetic Aperture Radar (SAR) (see Figure 5). SAR could be
air-, space-shuttle-, or satellite-born and is widely used in aboveground biomass estimation. The resolution of SAR is defined in two dimensions: range and azimuth. Unlike the old SLAR radar system, whose azimuth resolution is constrained by antenna length, SAR uses signal processing to increase azimuth resolution by hundreds of times (Canada Centre for Remote Sensing, 2008). For transmitting and receiving radiation, the orientation of the electromagnetic wave (polarization) is configured as V for vertical and H for horizontal (e.g. HH is horizontally transmitted and also horizontally received waves, while VH is vertical transmitted and horizontally received radiation). Besides backscatter of amplification in different bands, polarization is also an important characteristic of predicting aboveground biomass. The horizontal and vertical distribution of the target affects the backscattered amplification of the signal (Patenaude et al., 2005).

**Figure 5 Concept of synthetic aperture**


The interpretations of radar data mainly use regression on different variables. Properly polarized L-band SAR data are among the variables commonly used (Luckman et al., 1998; Castel et al., 2002; Sun et al., 2002).

The L-band HV (LHV) channel of the Shuttle Imaging Radar (SIR-C) data has been shown to be a strong predictor of aboveground biomass (Harrell et al., 1997; Sun et al., 2002). Likewise, the L-band HH SAR channel of the Japanese Earth Resources Satellite 1 (JERS-1) has shown a significant relationship between the backscatter coefficient of JERS-1/SAR data and the stand biomass of a pine.
Aboveground biomass estimation by radar data can achieve good accuracy in low and medium density forests, but the relationship between radar backscatter and aboveground biomass weakens when the forest becomes too dense, reaching saturation density. Saturation density is correlated with the wavelength of band, polarization, and characteristics of the vegetation canopy and ground conditions (Lu, 2006). For example, Ranson and Sun (1994) found that L, P-band HV data appeared to saturate at 150 tons per hectare in boreal forest, while Luckman et al. (1998) found that the L-band data saturated at 60 tons per hectare in rainforest. This variability can be attributed mainly to density saturation problems rather than real differences in forest type, and emphasizes the importance of being careful when comparing and using biomass estimates derived from different band data and technologies.

**LiDAR data**

Laser altimetry, or Light Detection and Ranging (LiDAR), is an active remote sensing method, analogous to radar, but it uses laser light instead of microwaves. The detection principle of LiDAR is similar to that of radar but is different in radiation frequency emitted. A pulse is generated with wavelengths in the visible or near infrared spectrum (900–1,064 nm), and the travel time from the sensor to the target on the ground and back is measured. Unlike optical and radar remote sensing methods, the LiDAR system provides direct information, such as the vertical structure of targets. LiDAR is therefore not actually producing images, so the data need to be converted to aboveground biomass estimations by more sophisticated models. LiDAR measurements are usually taken airborne by aircraft or helicopter (Patenaude et al., 2005).

There are two types of LiDAR systems that are distinguished by the information collected from the return signal: i) discrete-return devices (DRD); and ii) waveform recording devices (WRD). DRD can measure one (single-return systems) or a few (multiple-return systems) heights by identifying major peaks. WRD records the time-varying intensity of the returned energy from each laser pulse (Lefsky et al., 2002) (Figure 6). The DRD system has a high spatial resolution (5-90 cm) but provides limited information in stand vertical structure, while the WRD system has a low spatial resolution (10-25 m) but provides enhanced information about the vertical structure of forest.

Similarly to radar, LiDAR data are mainly used in regression models to estimate aboveground biomass. For example, studies by Nelson et al. (1997), Lefsky et al. (2002), and Drake et al. (2003) all used regression analyses to estimate aboveground biomass from mean canopy height. Wulder and Seemann (2003) tested the feasibility of using a regression model to spatially extend a LiDAR survey from a sample to a larger area with Landsat TM data. The height measured by LiDAR and correlated with Landsat TM are expected to complement the forest inventory data. At this stage, the regression models still need to be further developed (Wulder and Seemann, 2003).
The main potential of remote sensing is as a validation tool, rather than as a tool for producing the actual estimate of aboveground biomass, because field measurements are still needed.

Improvements for remote sensing methods

Remote sensing is a revolutionary technology for aboveground biomass estimation, with unprecedented capability of spatial, temporal, and spectral resolution and potential coverage of remote forest areas. If not restrained by cost, the data can be gathered from anywhere without political or regional restrictions, which overcomes a significant short coming of forest inventory methods for estimating aboveground biomass. Remote sensing data can also complement the conventional inventory data to increase the accuracy of models. However, to improve the utilization of remote sensing data in aboveground biomass estimation, there are several hurdles that need to be overcome.

Patenaude et al. (2005) suggest that the main potential of remote sensing is as a validation tool, rather than as a tool for producing the actual estimate of aboveground biomass, because field measurements are still needed (Fuchs et al., 2009). There are studies that have estimated aboveground biomass and compared results between inventory data and remote sensing data. In both cases MODIS and Landsat TM overestimate aboveground biomass compared with U.S Forest Inventory Analysis (FIA) (Zheng et al., 2007a; Wulder et al., 2008).

Many direct remote sensing estimations of aboveground biomass still cannot meet an acceptable accuracy without forest inventories. This could potentially be solved with better models, indexes, and instrumentation. An example of this would be...
Flux is the rate of flow of energy or particles across a given surface.

Further research on the study of effects of features such as mountains, slopes, and aspects. Such features are a major source of error, and can affect vegetation reflectance, resulting in spurious relationships between aboveground biomass and reflectance. Better estimates of aboveground biomass are always made where land surfaces are flatter.

In the past, remote sensing technology has been dominated by developed nations such as the United States. However, this dependence raises the cost and risk of obtaining data worldwide and provides an over-reliance on satellites from a single country’s remote sensing program. For example, reliance on the U.S. program has resulted in missed opportunities in data gathering with the failure of Landsat 6, defects in Landsat 7, the delay of LDCM, and the cancellation of vegetation canopy LiDAR. Remote sensing technology in more countries or consortiums is needed to provide the international community with more options in satellite imagery and radar/LiDAR data.

**EDDY COVARIANCE**

**Basic theory and advantages**

Since the late 1990s, the eddy covariance method has been developed in order to directly measure the uptake and release of CO₂ ($\text{CO}_2$ flux$^2$). This method samples 3-dimensional wind speed and CO₂ concentration over a forest canopy at a high frequency (around 10 to 20 Hz), and determines the CO₂ flux by the covariance of the vertical wind velocity and CO₂ concentration (Moore, 1986; Gash and Culf, 1996; Bosveld and Beljaars, 2001).

The relationship between i) CO₂ flux and ii) the covariance of vertical wind velocity and CO₂ concentration is derived by putting a hypothetical control volume (box) over a homogeneous canopy (Figure 7). On the upper surface of the “box”, three-dimensional wind speeds are recorded in a coordinate system that has the x axis aligned to the averaged wind direction. This assumes that one-dimensional flow (mean lateral velocity, mean vertical velocity) and stationary flow (no accumulation of CO₂ within the “box”) is obtained over a sufficient averaging period (30 min to 1 hr). The surface exchange of CO₂ should then be equal to CO₂ exchange at the upper surface of the “box”, based on the mass balance within the “box” (Finnigan et al., 2003). By measuring the vertical velocity of CO₂ flow at the height of the upper surface of the “box”, the eddy covariance method directly measures CO₂ fluxes over the forest canopy (Lee, 2004, Baldocchi and Meyers, 1998).

This method is favored because of its high accuracy and appropriate spatial scale. CO₂ flux is usually underestimated by less than 5% during daytime and less than 12% at night. A higher accuracy can be obtained by sampling at a finer temporal and spatial resolution. For example, given normal forest canopy roughness, flat topography, and calm meteorological conditions, an anemometer positioned at 30 m with a sampling interval that is averaged every 30 to 60 minutes should provide an accurate estimate of CO₂ flux that covers an area from a hundred meters to several kilometers (Berger et al., 2001).
Eddy covariance measurements have been continuously made at a number of sites for over ten years (Berger et al., 2001; Haszpra et al., 2005; Su et al., 2008). New observation sites, updated models, and remote sensing data enable the eddy covariance methods to continually refine estimates of CO$_2$ flux from regional to continental scales (Owen et al., 2007; Sasai et al., 2007; Yang et al., 2007; Yuan et al., 2007).

**Systematic biases**

Since the eddy covariance method is derived from assumptions such as homogeneous canopy, steady environmental conditions, and stationary flow, it suffers from many systematic biases that need to be accounted for.

**Energy imbalance**

For eddy covariance measurements, an imbalance exists of about 20% between turbulent energy fluxes (sensible and latent heat that is measured by the eddy covariance system) and available energy (net radiation minus stored energy that are measured separately with radiation sensors and soil heat flux plates) (Wilson et al., 2002; Han et al., 2003; Li et al., 2005).

The imbalance can be caused for three reasons: i) using 30 minutes as an averaging period in flux estimation filters out low frequency turbulence whose contribution to the flux model is missed (Foken et al., 2006); ii) flux measurements taken at different heights or across varying topographies represent CO$_2$ exchange from different source areas, with the result that the source area may not match the representative area separately measured for available energy (Schmid, 1997); and iii) the flux may not be fully detected due to advection or air drainage (Massman and Lee, 2002; Hammerle et al., 2007).
Although the CO$_2$ flux itself is not adversely affected by an energy imbalance, closing the energy budget is important for cross-site comparisons and a better understanding of underestimation and error in CO$_2$ flux measurement (Wilson et al., 2002).

**Nighttime flux**

The boundary layer at nighttime is characterized by low wind speed, thermal stratification, and intermittent turbulence. These characteristics always cause dramatic bias in CO$_2$ flux estimations (Aubinet et al., 2005; Velasco et al., 2005; Fisher et al., 2007). Vertical and horizontal advection are not negligible, but the correction for advection is usually site-specific (Feigenwinter et al., 2008). Due to thermal stratification, CO$_2$ concentration builds up within the air layer below the measurement heights, so the storage term can also be significant. But the correction of the storage term is controversial and site-dependent, because CO$_2$ stored at night might be released in the morning when advection can be negated (Aubinet et al., 2002).

**Topography**

Over sloping terrain, mathematical rotations of the wind coordinate system are used to meet the basic assumptions of one dimensional flow, but advection is unavoidable (Massman and Lee, 2002) and different rotation methods introduce different systematic errors to the estimation (Finnigan, 2004). Besides, CO$_2$ uptake measured at one point may be transported by drainage flows and emitted somewhere else (Sun et al., 1998).

**Data gaps and scaling up to regions and continents**

In addition to the three systematic problems that can lead to bias in estimates, sampling intervals can be interrupted by weather (e.g. heavy rain) and other unforeseen problems such as lightning strikes. A model based on a semi-parametric relationship between net CO$_2$ flux and environmental conditions, such as light and temperature, can be used to supplement and interpolate between such data gaps (Stauch and Jarvis, 2006). Data gaps from eddy covariance measurement exist not only with sampling period (time) but also over area (space). A single eddy covariance measurement can only represent flux over hundreds meters. Multiple observation sites and sophisticated models are required to develop an estimation of regional and global CO$_2$ budgets.

Since 1998, FLUXNET, a global-scale network for eddy covariance flux measurements, was started to encourage collaboration among flux measurement sites around the globe (Baldocchi et al., 2001) (Figure 8). It supports calibration and comparison of flux measurements among sites and supports collection of vegetation, soil, hydrologic, and meteorological data for each site. Using this network, FLUXNET provides a comprehensive dataset for expanding and scaling up CO$_2$ flux estimations from a single site to global and regional estimates. However, although the number of FLUXNET tower sites has expanded from around 100 to over 400 in the last decade,
most of the sites are located in temperate forest, grasslands, and shrubland, while measurement over some vegetation types such as tropical ever-wet and semi-evergreen rainforest, tropical dry deciduous forest, temperate rain forest, desert, urban areas, and tundra are noticeably under-represented.

Figure 8 FLUXNET sites in the climate space

Source: Site information is from http://daac.ornl.gov/FLUXNET/, biome lines are drawn from Barnes et al. (1998)

Scaling models up to extend flux measurements from single sites to a larger scale involves measurements of two main processes: canopy photosynthesis and ecosystem respiration (Running et al., 1999; Soegaard et al., 2000; Wang et al., 2007b; Baldocchi, 2008). Models can be divided into two categories: i) empirical models which are based on the relationship between CO₂ flux and plant eco-physiological parameters (e.g. photosynthetic light response curves); and ii) physiological growth models based on stand dynamics (Owen et al., 2007). Both categories of models can be parameterized by eddy covariance measurements, but the parameters can change considerably among different models and different ecosystems. Strong relationships between CO₂ uptake and leaf area index have been utilized in the European Arctic region to calculate spatial distribution of Net Ecosystem Exchange (CO₂ flux) based on Landsat TM satellite data (Soegaard et al., 2000). Still others have proposed that net ecosystem exchange may be characterized mainly by non-climatic conditions (e.g.
species, age, and site history) (Ball et al., 2007; Luyssaert et al., 2007). In a temperate moist broadleaf and coniferous forest in North Carolina, USA, parameters such as leaf nitrogen concentration and stomatal conductance were measured as inputs to a physiologically based canopy model to estimate gross primary productivity (Luo et al., 2001). Additionally, at observation sites located over heterogeneous landscapes, a footprint model has been used to determine the source area of eddy covariance measurement (Schmid, 1997; Soegaard et al., 2000; Chen et al., 2007).

Figure 9 CO₂ fluxes from estimation using TransCom-3 inverse model setup and 16 global transport models. Black circles mark the average fluxes obtained from 16 models, black lines show between-model uncertainties and red thick lines show within-model uncertainties. For each panel, left part is derived from ‘all site’ data; right part is derived from ‘ocean-only’ data.


In summary, eddy covariance is a promising method for both CO₂ flux measurements at a regional scale and CO₂ budget estimations at global scales. But more research needs to be conducted to close the energy budget and eliminate biases caused by night time stratification and complex topography. In addition, more sites are needed over various vegetation types that can be calibrated to other sites.
**INVERSE METHOD**

Atmospheric CO₂ concentration can be estimated from sink and source measurements of carbon (forest inventories, flux measurements) combined with transportation models (that model gas movement) using meteorological information. It can also be measured directly. The inverse method has been developed to indirectly calculate sinks and sources of CO₂ from the measured concentration by using the Bayesian inversion technique (Gurney et al., 2002; Rodenbeck et al., 2003). This technique backs out carbon sources and sinks of trace gases including CO₂ through the use of three-dimensional transport models (Gurney et al., 2002) – hence the so-called inverse method. Transportation models and atmospheric CO₂ concentration data therefore determine the accuracy of the inverse method (Patra et al., 2006). Sixteen different transportation models, along with a variety of atmospheric CO₂ datasets, have been used to test, calibrate and estimate regional to continental scale carbon flux (Figure 9). ‘Between-model’ uncertainties are about 0.51Pg C per year, and are generally smaller than ‘within-model’ uncertainties.

The reader should be aware of the following caveats:

1. All models work better over oceans than over land.
2. Different datasets can lead to large differences in estimation. The more sites used in an inverse model, the lower the ‘within-model’ uncertainty. For example, large uncertainties in the tropical zone data reflect the few observations that are conducted there.
3. Using ‘ocean-only’ data (excluding the land and coastal measurement sites) instead of ‘all site’ data leads to better agreement between models, but the ‘within-model’ uncertainties increase.
4. Big meteorological or geological events, such as El Niño or a volcanic eruption, bias the data, leading to poor estimation.

With the development of more comprehensive datasets and improved transportation models, CarbonTracker, developed by NOAA’s Earth Systems Research Laboratory, has emerged as one of the most advanced inverse models used today (Figure 10). Over the domain covering North America and the eastern Pacific, very good agreement has been achieved between CarbonTracker predictions and real atmospheric measurements (Peters et al., 2007).

CarbonTracker is constrained by about 28,000 flask data points collected by the NOAA ESRL Cooperative Air Sampling Network and continuous CO₂ time series observed at several towers (Peters et al., 2007). Data processing consists of the following steps: i) develop a 3-dimensional field of atmospheric CO₂ mole fraction around the globe by coupling CO₂ surface exchange models (ocean module, fire module, fossil fuel model and biosphere model) (NOAA, 2008) with an atmospheric transport model TM5 (Peters et al., 2004; Krol et al., 2005); ii) minimize the difference between modeled and observed CO₂ mole fractions by adjusting linear scaling factors which control surface fluxes for large areas; and iii) build up the history of surface CO₂ exchange at the latitude-longitude resolution of 1°×1° (Peters et al., 2007).
While measuring CO₂ concentrations, many sites also take measurements for other trace gases (e.g. methane, nitrous oxide, sulfur hexafluoride, carbon monoxide, isotopic ratios of CO₂ and methane). The additional measurements are not only related to climate change, but also can help in source identification of CO₂. Halo-compounds (an organic compound that includes a halogen – e.g. chlorine, fluorine) and hydrocarbons (an organic compound consisting entirely of hydrogen and carbon) have recently been added to the analysis of a subset of air samples along with carbon-14, the best trace for CO₂ emitted through use of fossil fuels.

Although CarbonTracker is an improvement over other inverse models in many aspects, it also suffers from some problems:

1) The accuracy of CarbonTracker depends on the quality and number of observations available. CarbonTracker’s ability to accurately quantify natural and anthropogenic emissions and uptake at regional scales is currently limited by a sparse observational network.

2) Predicted burned area does not match with the observed one in some regions. Methods for dealing with heteroskedastic variables through weighted least
squares or nonlinear data transformations increase the influence of low-variance observations while simultaneously decreasing the influence of high variance observations. This is undesirable for estimation (Giglio et al., 2006). Improvements need to be made in the estimation of small burned areas, although they are of less interest compared to the large burns.

3) In the current version of CarbonTracker, relatively small errors in fossil fuel emissions inventories are averaged out by relatively larger errors in other flux emissions (e.g. fires) (Peters et al., 2007).

In order to keep improving this tool for monitoring and predicting the global carbon cycle, all results from CarbonTracker are freely accessible, joint observations are encouraged, and models are updated every year. In addition to the simulated 3-dimensional field of atmospheric CO$_2$, direct measurement of the 3-dimensional field from satellites is now available (Rayner and O’Brien, 2001). The satellite sensors are the Atmospheric Infrared Sounder (AIRS) and the Scanning Imaging Absorption Spectrometer for Atmospheric Cartography (SCIAMACHY) (Buchwitz et al., 2007). In 2008, two dedicated missions called the Orbiting Carbon Observatory (OCO, National Aeronautics and Space Administration) and GoSat (Japanese Space Agency) were launched to quantify CO$_2$ (Peters et al., 2004). More advanced measurements and more data will improve the performance of CarbonTracker dramatically.

**CONCLUSIONS AND RECOMMENDATIONS**

The four categories of methods reviewed in this chapter are based on biomass measurement data, remote sensing data, CO$_2$ flux data (from eddy covariance) and CO$_2$ concentration data. They all exhibit their own advantages and disadvantages in estimating CO$_2$ flux and complement each other in different ways (Table 4; Figure 11).

<table>
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<tr>
<th>Methods</th>
<th>Temporal Scale</th>
<th>Spatial Scale</th>
<th>Data Availability</th>
<th>Uncertainty</th>
<th>Target</th>
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<tr>
<td>Forest Inventory</td>
<td>Annual and decades</td>
<td>Regional</td>
<td>Historical data worldwide</td>
<td>1% for growing stock volume, 2 to 3% for net volume growth and removal, and almost 40% for change in growing stock volume.</td>
<td>Carbon stock in the forest</td>
</tr>
<tr>
<td>Remote sensing</td>
<td>Daily to annual</td>
<td>Regional and Global</td>
<td>Start from the end of 1970s</td>
<td>The RMSE for an aggregation area of 510 ha of forest land was 8.7% for AGB and 4.6% for wood volume.</td>
<td>Carbon stock in the forest</td>
</tr>
<tr>
<td>Eddy covariance</td>
<td>Hours to years</td>
<td>Over the course of a year or more</td>
<td>Start from end of 1960s; over 400 sites worldwide</td>
<td>$-50gCm^{-2}yr^{-1}$ (ideal site)</td>
<td>Net CO$_2$ exchange across the canopy-atmosphere interface</td>
</tr>
<tr>
<td>Inverse Method (Carbon Tracker)</td>
<td>Weekly</td>
<td>Global, at 1º x 1º resolution</td>
<td>2000-2006</td>
<td>-0.65PgC/yr (for North American terrestrial biosphere)</td>
<td>Access net CO$_2$ exchange between the terrestrial biosphere and the atmosphere</td>
</tr>
</tbody>
</table>

Source: Compiled from Brown, 2002; Patenaude et al., 2005; Lu, 2006; Baldocchi, 2008; Giglio et al., 2006 and Peters et al., 2007
Inventory methods quantify biomass accumulation within forests, and are characterized by their long history and adequate data coverage (particularly in developed nations). However, they have low time resolution (years) and variable standards of measurement.

Remote sensing methods are most reliable if remote sensing information is jointly used with forest carbon inventories and ecosystem models. However, incomplete information limited by remote sensing techniques and uncertainties in the models require further development.

The eddy covariance method is advanced in its high accuracy and fine temporal resolution (hours), and is a good method for direct measurement of CO$_2$ flux at the ecosystem scale. However, it is restricted in use by its systematic biases and limited number of observation sites.

Inverse methods are used at continental to global scales. They retrieve the strength of both anthropogenic and non-anthropogenic sources and sinks from atmospheric CO$_2$ concentration data and transportation models. CarbonTracker is one such inverse model. The data assimilation models in these inverse methods are being improved for higher accuracy and finer spatial resolution.

No single method can meet the accuracy and resolution requirements of all users. A country, user or site will make a choice of method based on the specifics of the circumstance. To accelerate improvements, the user is encouraged to undertake data comparison, collaboration, and assimilation among different methods (Heinsch et al., 2006; Gough et al., 2008). Such improvements should build on a careful synchrony among methods. For example, CO$_2$ budget estimations from forest inventory are based on biomass accumulation, while CO$_2$ flux measurements reflect photosynthesis and
respiration – usually a one-year time lag will be found between these two results. In addition, a finer and more comprehensive observation network of CO2 concentration is required.

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