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REMOTE SENSING (P BUNTING, SECTION EDITOR)

Characterizing Forest Growth and Productivity Using Remotely Sensed Data

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Abstract Forest growth and productivity are critically important at a range of spatial scales, to better understand the terrestrial carbon cycle globally to sustainably manage the forest locally. Field measurements of forestry parameters to assess productivity at any spatial scale consume substantial resources in terms of both time and cost. Remote sensing enables a highly accurate approach for observation of forested ecosystems, providing the tools to estimate many biophysical parameters across a range of scales. There are a number of different methods of measuring the productivity of forested ecosystems using remote sensing. In this review, we summarize the three general approaches—productivity via physiological measurements, dimension analysis, or relationships of growth to foliage concentrations and light—and provide specific examples throughout on the use and application of remote sensing technologies. The paper concludes with some general statements on future work and the way forward.

Keywords Forest growth · Remote sensing · Terrestrial carbon cycle · Forested ecosystems

Introduction

Information on forest production is critically important for a wide range of environmental applications. At global scales, information on the growth of forests is critical for calculations related to the terrestrial carbon cycle. Forests have been estimated to absorb up to one quarter of carbon emissions from fossil fuel combustion (2.8 Gt C year^{-1}) [1]; however, uncertainties are large with significant variation both spatially and temporally, in particular in photosynthesis with even small differences in forest productivity across the globe likely to have marked impacts on overall carbon sequestration rates [2, 3]. Forest growth information is also critical for sustainable management [4], allowing managers to assess both current and future yields of forest stands. This, in turn, has economic implications for regional and national forest-dependent economies and their associated industries. In addition to these global climate and regional economic drivers, sustained forest productivity supports a range of ecosystem goods and services, such as the provision of clean water, carbon storage, and biodiversity. This increasing need for information on the growth and productivity of forest ecosystems globally has resulted in high demands for accurate, timely, and comprehensive information at global, regional, and local scales.

Field measurements of forestry parameters to assess productivity at any spatial scale consume substantial resources in terms of both time and cost. Over large spatial and temporal scales, these field measurements are virtually impossible [5–7]. Remote sensing enables a highly accurate approach for observation of forested ecosystems, providing the tools to estimate many biophysical parameters across a range of scales. In fact, it could be argued that remote sensing is the only technology able to offer repeatable and consistent observations on the role of vegetation and its productivity across the globe [8]. Indeed, we may be today in the golden age of remote sensing, with a panoply of satellite systems, sensor types, and largely free and open data access policies that facilitate the widespread application of remote sensing, making access easier than ever before. However, with this diversity of data comes potential confusion: different types of sensors

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provide different indicators of forest productivity and combined with a range of complex interpretation techniques results in many types of remote sensing products relevant to forested landscapes [9]. Additionally, no single remote sensing platform or system can meet the needs of all researchers and managers interested in forestry production, as each platform has specific limitations and capabilities [10•]. As a result, it is important for remote sensing specialists and forest managers alike to have a thorough understanding both of different sensors' capabilities and of the general approaches used to test and assess the predictive strength of the biophysical or forest inventory parameters under consideration.

Traditionally, from an ecological perspective, forest productivity can be viewed through a set of environmental constraints which, when overcome, allow productivity to be maximized. Factors such as climate, precipitation, soil chemistry, and topographic position are all regarded as key variables placing environmental constraints on production [11, 12]. Conversely, a forest stand may be categorized by potential wood production through developing relationships between structural attributes, age (if known), and dominant species. From this, growth rates from yield tables and models can be derived [13, 14]. Despite these underlying relationships, links between the environment and forest productivity, and growth and forest productivity, are generally site and species specific.

Measurements of Forest Productivity

There are a number of different methods of measuring the productivity of forested ecosystems. These methods can be segregated into three general approaches: productivity via physiological measurements, dimension analysis, or relationships of growth to foliage concentrations and light (Fig. 1). Each approach is explained in detail below.

Productivity via Physiology

The gross primary production (GPP) of vegetation is the amount of organic matter synthesized and accumulated in tissue per unit of time plus the amount used by plant respiration or the product of the absorbed photosynthetically active radiation (APAR) and the vegetation light-use efficiency (LUE). LUE is often considered to represent the efficiency that the foliage can use APAR to produce biomass [15••]. The GPP, less the respiration, is known as the net primary production (NPP) [16, 17]. One of the most commonly applied methods for measuring GPP is using eddy covariance (EC) techniques. This technique exploits the covariance between fluctuations in the CO_2 mixing ratio in the air column with the vertical wind velocity above the canopy to predict the carbon fluxes [18]. A number of limitations exist when using the EC method; first, the underlying theory behind EC assumes uniform conditions within the local environment, principally within radius of the EC footprint (a few hundred square metres to a square kilometre) specifically in the upwind direction [18], which is known to be often violated in complex forest stands, particularly over changing topography. Second, the size of the footprint is large making GPP estimates of a single tree or small stand impossible. Finally, GPP can be derived from net ecosystem production (NEP) only if ecosystem respiration is known. As a result, remote sensing opportunities to measure and monitor GPP are numerous.

Productivity via Dimension Analysis

The most common approach to estimate forest growth is by developing relationships between growth and direct measurements of the size and weight of plants or plant parts [16, 17]. These relationships are often developed by dividing a forest stand into components such as trees greater than 10-cm diameter; understorey and shrubs; and ground cover, each of which is considered separately. A sampling programme is then designed typically involving one or more types of samples: non-

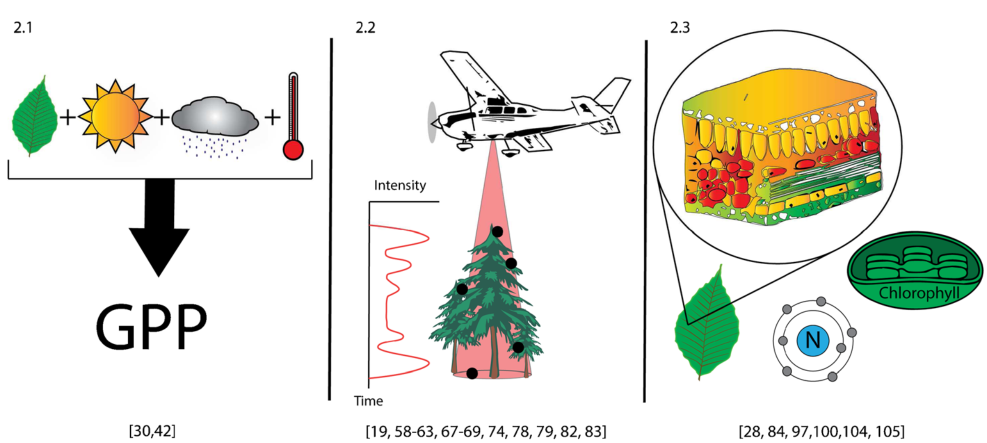

Fig. 1 Three general approaches of assessing forest productivity using remote sensing approaches: productivity via physiological measurements, dimension analysis, or growth relationships with foliage concentrations and light. Sections within this review are indicated on the *top left*, relevant papers on the *bottom*

destructive measurements (e.g. diameter, height), destructive measurements which could involve the dissection of branches and boles and partitioning them into leaves and small branches and estimating their dry weight or volume, and measurements of litter fall. Regression analysis is used to obtain correlations between the field measured variables and the attributes of interest such as total (or change in) biomass and volume. In many cases, forest productivity is estimated using only the direct measurement of boles themselves with indices such as current annual increment (CAI; i.e. the annual change in a forest attribute); the increment for a given period of time or periodic annual increment (PAI); and the mean annual increment (MAI), which will all vary according to the age and growing conditions of the stand [19].

Productivity via Light and Foliar Concentration

Third, estimates of forest growth can be obtained through the development of indices that relate to the individual plants' foliage properties which are assumed to correspond to the overall functioning and plant condition. One of the most common indices is the leaf area index (LAI), defined as the mean leaf surface area above a square metre of ground surface [20]. For a given species or stand, there are strong relationships between LAI and productivity. LAI has been shown to be a highly effective expression of productivity and is more directly expressive of the photosynthesis of the vegetation. Leaf chlorophyll content and/or concentration has also been shown to be an effective indicator of vegetation productivity, developmental stage, and stress [21, 22]. In poor production vegetation, the chlorophyll content of leaves decreases, thus changing the proportion of light-absorbing pigments resulting in a reduction in overall light absorption [23]. Like chlorophyll, foliar nutrient content is also a key indicator of forest productivity with a range of studies highlighting consistent and strong, generalizable relationships between foliar nitrogen for example and the rates of net photosynthesis and leaf respiration of forest vegetation. Foliar nitrogen has been shown to then link to canopy-level nitrogen which at broader spatial and temporal scales is related to annual net primary production and soil nitrogen mineralization [24–28]. As a result, estimates of foliar nitrogen can provide insights into terrestrial carbon and nitrogen cycles and can be a useful indicator and input variable into models of forest and ecosystem productivity [27, 29••].

Forest Productivity Estimates Using Remotely Sensed Data

Each of these three approaches for assessing forest productivity can be used in combination with remote sensing to provide estimates over large spatial scales and at lower cost than field measurements. A summary of these approaches is shown in Table 1.

Physiology

GPP/NPP

Global estimates of the incoming photosynthetically active radiation (PAR) can be derived from satellite observation using top-of-atmosphere measurements of solar radiance and modelling approaches [31]. The fraction of PAR (fPAR) that is absorbed by plants to provide the energy input depends on the LAI of the vegetation, which can also be estimated from satellite observations (see later section). A large number of studies at a variety of scales [32–34] have demonstrated the relationship between APAR and the visible and near-infrared regions of the electromagnetic spectrum using, for example, the normalized difference vegetation index (NDVI [32]). Using these relationships in the mid to late 1980's, researchers applied NOAA AVHRR imagery to predict vegetation productivity for Africa [35], North America [36], and the entire world [37]. Goward et al. [38] first related the NDVI to NPP and developed LUE factors to convert the annual APAR energy to NPP for different biome types. Box et al. [39] evaluated the accuracy of AVHRR-derived vegetation indices as a predictor of biomass, primary productivity, and net CO_2 flux. The launch of MODIS on TERRA and AQUA led to the MODIS GPP product (MOD17), described in detail by Running et al. [30•], which also relies on the LUE approach to model productivity using fPAR and ground station meteorological data. In this approach, the maximum LUE is dependent on vegetation type and is reduced by multipliers based on climate including cold temperatures and vapour pressure deficit (VPD). Heinsch et al. [40] showed that MOD17 GPP product had a relatively strong correlation to EC estimates of GPP across North America (r=0.859±0.173), but overestimated tower estimates at most sites (relative error=24 %). Global mosaics of monthly GPP and annual NPP are now routinely available for analysis [41].

Building on the LUE principles, other models using satellite observations have been developed that also predict forest productivity. For example, the 3-PGS (Physiological Principles Predicting Growth from Satellites) model [42] is a simplified version of the original implementation of the 3-PG model [43••] and is driven primarily by vegetation light absorption, which determines the potential physiological rates. 3-PGS also estimates APAR as the product of PAR and fPAR, estimated from satellite-derived indices. 3-PGS then calculates the utilized reduced portion of APAR by the most constraining environmental modifiers which include (a) daytime atmospheric VPD, (b) soil water availability, and (c) the frequency of sub-freezing temperatures (<−2 °C). APAR is also further reduced by non-optimal temperatures that reduce the LUE. Availability of nutrients, specifically nitrogen, is modelled using a soil fertility modifier. Unlike the MODIS GPP algorithm, 3PGS utilizes a soil water balance model to

Table 1 Summary of approaches and remote sensing data used to derive forest productivity indices

Variable	Spatial scale	Typical sensor	Cost (USD)	Reference
Physiology				
GPP/NPP	Regional to global	TERRA MODIS AQUA MODIS SPOT VEGETATION	Free	[30•, 42]
Dimension analysis				
Height/diameter	Regional to local	Landsat TM LiDAR	Free $3–$5 Ha	[19] [58–61, 62••, 63]
Volume/biomass	Regional to local	LiDAR RADAR	$3–$5 Ha <$1 Ha	[67–69] [74]
Stocking/crown dimensions	Local	RapidEye, DigitalGlobe LIDAR	$1–$ 3 Ha	[78, 79]
Productivity via light and foliar concentration				[82, 83]
Chlorophyll	Regional–local	CASI, AVIRIS, HYPERION	$3–$5 Ha	[97, 100]
Nitrogen	Regional–local	CASI, AVIRIS, HYPERION		[28, 84]
LAI	Global–local	Landsat TM MODIS		[104] [105]

calculate water stress as the difference between total monthly rainfall, plus available soil water stored from the previous month, and transpiration, calculated using the Penman-Monteith equation with canopy conductance modified by the LAI of the forest [44].

Forest Dimensions

Diameter and Height

Large-scale aerial photography (1:200–1:3000) was the first remote sensing technology to be used to estimate forest dimensions, principally height and volume, often in a fraction of the time and cost of traditional field surveys. For example, in the 1970s and 1980s, researchers in Canada established sampling approaches using large-scale photography to predict volume. Hall et al. [45] utilized 12 diameter production models and large-scale aerial photography (1:1000) to model relationships between tree height, crown area, and diameter over a variety of species including white spruce and lodgepole pine. Results indicated that for all measured tree species, aerial photography-derived tree heights were not significantly different from felled measurements. These results were similar to those reported from Titus and Morgan [46] who investigated height estimates from tree felling and large-scale aerial photography. Again using photography, in the Yukon, Canada, measurements were found not to be significantly different from felled heights. The standard deviations of field and photo height errors were 0.95 and 1.17 m, respectively.

With the availability of satellite imagery from the Landsat series of satellites in 1972, mapping of forest productivity, such as height and volume, significantly increased. Cook et al. [19] investigated the usefulness of Landsat Thematic Mapper (TM) and biogeographical data to estimate productivity in three sites in the USA. Forest productivity was measured by indices of productivity (e.g. bole increment). Results showed that, in general, the regression and classification models were highly significant; however, they left a considerable amount of the variance unexplained, with low correlations ranging between 0.27 and 0.42. As a result, Cook et al. [19] concluded that approach could be used to model productivity of a region (<1000 km^2) with a high degree of confidence using both spectral and biogeographical data (such as soil productivity and solar insolation); however, the reliability of single pixel estimates would be poor. This finding generally remains true across many studies, due to the non-linear and complex relationships between forest structure and reflectance in the visible and infrared regions of the spectrum. A complementary approach to relating the spectral and spatial responses from remotely sensed data to forest height and diameter is through the development of numerical models that attempt to model the tree geometry from the images themselves. Strahler and Li [47, 48] proposed models that assume trees are widely spaced cones, surmising that reflectance measured by the satellite sensor is a mixture of shadow, understorey, and tree crown. The model was used to estimate tree stocking and height in sparse to moderately stocked ponderosa pine plantations using Landsat imagery. The model was found to have produced responses within 10 % of the true measured values. In a related study, Franklin et al. [49] used a similar model to simulate canopy reflectance of woodland and savannah in the Sudan and Sahel. In this modified model, the trees were hemispheres on sticks—not inverted cones as in Strahler and Li's [48] model. The results showed a correlation between the observed and predicted values of tree density and height greater than 85 %. The approach continues to be used in a diverse range of locations such as Queensland, Australia [50], and British Columbia [51].

Aerial photography and satellite imagery, both of which rely on measuring the reflectance from the sun, are known as passive remote sensing systems. In contrast, active remote sensing approaches, such as Light Detection and Ranging (LiDAR) and Radio Detection and Ranging (RADAR), send light or radio wavelengths, respectively, to the Earth's surface and measure both the time taken for the emitted pulse to return to the sensor and the backscatter of the emitted signal. LiDAR uses pulsed lasers to measure the distance to objects on the Earth and comprises three main components: the laser, an inertial navigational measurement unit (IMU), and a global positioning system (GPS) unit with airborne units using either helicopter or airplane platforms [52, 53]. In the case of LiDAR, the measurement of the return interval allows for the direct detection of the three-dimensional distribution of vegetation canopy components as well as sub-canopy topography, providing both high spatial resolution topographical information as well as highly accurate estimates of vegetation height, cover, volume, biomass, and other aspects of forest productivity.

LiDAR systems can record either discrete returns or the full waveform of the return pulse. Discrete return LiDAR systems typically record up to five returns per laser footprint [54] and are optimized for the derivation of sub-metre accuracy terrain surface heights [55, 56]. Full waveform LiDAR systems acquire a fully digitized returned pulse providing sub-metre vertical profiles. If the LiDAR data is acquired at a very high density (dependent on the number of LiDAR pulses per metre), individual tree crowns can be readily observed. Computer-based algorithms can be applied to automatically identify tree crowns and extract individual tree attributes such as total height, crown height, and crown diameter [57•]. With respect to height, studies have demonstrated that the error for individual tree heights of given species is <1.0 m [58] and <0.5 m for plot-based estimates of maximum and mean canopy height (although this accuracy is also dependent on the terrain, the density of canopies, and the mission parameters) [59–61, 62••, 63]. LiDAR estimates of height have been shown to be more consistent than manual, field-based measurements [61].

Volume

The use of satellite passive remote sensing data to predict stand volume, like height, is limited. Accuracies are generally too low to be of practical value for operational forest management planning [64]. Horler and Ahern [65] examined Landsat TM data to estimate volume in Canadian boreal forests. They found the red, NIR, and SWIR spectral bands were most correlated with changes in stem volume. However, the approach was limited to stands less than 60 years old. Trotter et al. [66] also used Landsat TM imagery to predict volume of New Zealand *Pinus radiata* plantations, reporting errors greater than 25 %. In addition, many studies have highlighted the issue with shadowing and its dominating effect on much of the spectral response.

Estimation of volume from LiDAR data is best achieved using the area-based approach [62••], which has become the standard procedure for processing LiDAR point cloud data. In this approach, LiDAR hits are accumulated within a given area (such as within the plot dimensions) and statistical properties of these point clouds derived and through empirical relationships related to a range of plot-level attributes (e.g. volume, basal area, biomass). This area-based approach has been shown to be highly stable across many forest types, ages, and structures due to LiDAR point clouds' being a detailed measurement of all reflecting surfaces within a canopy (i.e. foliage, branches, and stems) [57•]. Airborne LIDAR was applied as early as 1980 to predict forest volume [67] and has since been applied in diverse jurisdictions including Scandinavia, Finland, USA, Canada, and Australia [62••, 68–70].

In addition to LIDAR, RADAR offers potential to map forest volume and biomass from both space-borne and airborne platforms, especially at lower biomass sites. Early studies by Le Toan et al. [71] and Dobson [72] examined the RADAR backscatter from various forests stands. To date, the majority of studies investigating the use of RADAR data for biomass estimation have focused largely on coniferous forests particularly in North America, Eurasia, Australia, and some tropical regions which have generally been found to be successful due to the penetrative capacity of microwaves. However, using single polarized data, C, L, and P-band data has been shown to saturate at biomass levels of 20–40, 60–100, and 150 Mg ha^{-1}, respectively [73]. In Queensland, Lucas et al. [74] evaluated the use of multi-frequency RADAR data for quantifying open eucalypt forests and woodlands biomass. They concluded that L-band HV backscatter data acquired at large incidence angles (45° or greater) was best correlated with biomass up to 80–85 Mg ha^{-1} [74]. Single-pass X-band InSAR data has also been used to volume and biomass with Solberg et al. [75], utilizing InSAR stand height estimates in the boreal regions of southern Norway to predict biomass with no apparent saturation effect.

Stocking and Crown Dimensions

When the spatial resolution of optical imagery increases to the point that multiple pixels are evident within single tree crowns, individual tree detection allowing direct tree counting is possible, as well as the estimation of individual crown attributes. This type of information can be used by the forest managers to estimate overall stand productivity and has been demonstrated to be useful in forest management decisions, such as the timing of silviculture activities including pruning, thinning, and harvesting, particularly in plantation forestry [76]. With the advent of very high spatial resolution satellite and airborne imagery, individual tree detection algorithms have increased in number, complexity, and overall accuracy. With nominal resolutions <4 m, the capacity now exists to map and monitor forest patterns in greater detail [77]. A general rule is that the spatial resolution of the imagery should be much greater than the size of tree crowns (more than 9 pixels per crown), with aerial or satellite imagery having spatial resolutions between 10 and 4 m preferred [78]. Tree crown detection and delineation algorithms can broadly be categorized as local maxima/minima, template matching, region growing, and edge detection approaches, with each using different approaches to either delineate trees and/or delineate crowns [79, 80•]. Culvenor [80•] developed an individual tree detection routine for aerial digital camera imagery and found the approach was best suited to trees which have well-defined crown, noting that individual tree crown delineation from remotely sensed imagery is not a realistic expectation—even for human interpreters—in structurally complex forests. The study cited variations in viewing and sun angle which inhibit the ability to achieve repeatable results. The widespread use of LiDAR data today has allowed further improvements with the apex of the crown being more easily assessed using LIDAR data then passive imagery. As a result, the use of a LIDAR canopy model as input to these existing routines has been shown to improve tree detection and crown metrics markedly [81–83].

Leaf Properties

Progress in the past decade in imaging spectroscopy has allowed high spectral resolution remote sensing to become a viable approach to monitor canopy constituents. Hand-held, airborne, or space-borne imaging spectrometers are able to capture reflected light across the full electromagnetic spectrum at very fine spectral resolution, facilitating detailed analysis of narrow absorption features, in a more comprehensive way than more conventional, broad-band sensors such as Landsat and MODIS [84]. A range of techniques are available to derive pigment and nutrient concentrations from foliage including empirical approaches largely dependent on developing relationships between discrete spectral reflectance bands while minimizing viewing angle and soil background effects [85, 86]. More analytical techniques can use imaging spectroscopy to infer biochemical properties using radiative transfer models and estimates of leaf optical properties [87]. Among the most important biochemical compounds in terms of forest productivity are chlorophyll and nitrogen, both of which have been directly related to the photosynthetic capacity in plants [84, 88].

Chlorophyll

Variations in foliage chlorophyll content is a key indicator of forest productivity [22, 89], as in less productive sites vegetation leaf chlorophyll content decreases. This in turn changes the proportion of light-absorbing pigments and leads to less overall absorption [23]. Chlorophyll concentration in foliage absorbs red wavelengths (680 nm) while the placement and shape of the transition between red absorption and near-infrared reflectance (known as the "red edge", the region between 690 and 740 nm [89]) is also highly sensitive to chlorophyll content [89–91]. A number of papers have developed indices that can be applied across a range of forest structural and productivity gradients. For example, Datt [92] developed a series of chlorophyll indices suitable for eucalypt vegetation at both the leaf and stand level, and Barry et al. [93] utilized hand-held spectra to assess if reliable and robust methods of spectral analysis can be developed for detecting chlorophyll of plants under stress in commercially important forest production species.

Nitrogen

Nitrogen, like chlorophyll, is a key indicator of forest productivity and an important limiting factor in many forested areas of the globe. It is also a critical nutrient for crop monitoring and yield estimation [94]. As compared with absorption features in the visible and near-infrared spectrums, nitrogen content absorption features occur in the short-wave infrared (SWIR) portion, and as a result, imaging spectroscopy with capacity in the 1100–2500-nm range is often viewed as important for detection of the nitrogen signal in forested vegetation. However, vegetation with limited nitrogen uptake will also have lower chlorophyll content, which stands as an indicator for non-optimal photosynthesis [95]. Imagery from the (now decommissioned) Earth-Observer-1 Hyperion sensor and AVIRIS, an airborne imaging spectrometer (research-based instrument designed and managed by NASA), have both been used to generate predictions of nitrogen content within 0.25 % of ground estimates, meeting the needs for accurate spatial estimates of nitrogen concentration for environmental studies in the eastern USA [96]. Coops et al. [97] and Coops et al. [98] demonstrated the use of Hyperion image data for mapping nutrient concentrations in *Eucalyptus* and *Pinus* species. These models initially focused on nitrogen, but Coops et al. [97] also mapped the concentration of 11 macro- and micronutrients in a pine stand. Similarly, Sims et al. [99] mapped the concentration of 12 macro- and micronutrients in a Queensland exotic pine estate using a variety of least squares methods [100].

Leaf Area Index

Rather than estimation of the pigment and nutrient concentration of the foliage itself, the amount of foliage (measured as the leaf area index or LAI) of stands is also a key indicator of forest productivity principally due to its importance for photosynthesis, transpiration, evapotranspiration [101], and, in turn, GPP. LAI is also a key input in ecosystem models that simulate carbon and hydrological cycles [102], with Running et al. [103] being among the first to couple estimates of LAI with extrapolation and simulation models that predict forest productivity. Remote sensing estimation of LAI has been undertaken using a number of approaches. The most widely used relationship is that between LAI and NDVI. Curran et al. [104] related Landsat TM NDVI data to seasonal LAI for regions of slash pine in northern Florida. A number of forest structural variables were collected for 16 plots, and biomass for each plot was calculated by selectively felling a proportion of trees within each DBH class. LAI was developed from the biomass estimates. Linear relationships were developed between NDVI and LAI, with r^2 values ranging from 0.35–0.86. LAI is now routinely produced as a biophysical attribute from MODIS, SPOT, and other remote sensing satellite systems, and as a result, algorithms have become more comprehensive and now include both red and near-infrared surface reflectances, as well as information on view/illumination geometry and land cover [105]. This is supported by compositing techniques developed to produce 8-day and monthly LAI estimates.

Summary and Future Research

The past decade has seen significant advancement in research and applications in a wide suite of remote sensing technologies to assess forest productivity. Previously, the use of single remote sensing scenes, such as Landsat TM imagery, or the limited use of time series of coarser spatial resolution imagery has hampered widespread use and adoption of remote sensing indicators of forest growth at regional or global scales. More recently, the widespread use of MODIS data and the ongoing building of a long-term data archive, as well as the ready availability and free access to Landsat imagery, have seen an increased appreciation for the use of long-term data series in predicting a range of forest attributes. As a result, we are seeing a strong movement away from simple indicators of forest growth (e.g. NDVI) towards more complete and analytical radiative transfer solutions, which allow issues such as terrain, atmospheric effects, and sensor degradation to be minimized. In addition, the use of complementary spatial data, such as terrain, climate, and geographical variables, with remotely sensed imagery has been shown to significantly improve attribute prediction either directly or through stratification approaches. Likewise, integration with forest inventory data within forest management systems will also improve long-term prediction of forest growth and other attributes.

The increasing availability of different types of high spatial resolution satellite and airborne imagery has facilitated novel approaches to directly count trees and predict crown attributes, both of which can be used to infer growth rates of key species. Additionally, algorithms designed to detect individual trees from optical and LiDAR data are more commonly capitalizing on pattern recognition and data visualization techniques to help remove some of the ambiguity associated with traditionally exclusively spectral-based classification techniques.

The rapid advancement of LiDAR data has seen the derivation of highly detailed individual tree-level and plot-scale data, consequently revolutionizing forest stand characterization and enhancing our capacity for acquiring biophysical and ecological variables for forest planning and operations [106•]. LiDAR technology and methods are now being implemented in the world's forests, providing critical information on tree and stand volume, cover, height, and structure. Into the future we may see satellite and other space-based LiDAR missions which will greatly expand the reach and use of LiDAR globally.

Within the next 5 years, ongoing research remains critical to continue to provide forest managers and scientists working in environmental and natural resources fields with timely and accurate estimates of forest productivity. Key challenges include the following.

Continuity with VIIRS

At the broad spatial scale, the MODIS sensor onboard TERRA and AQUA will be nearing the end of their expected lifetime within the next 5 years. The Visible Infrared Imaging Radiometer Suite (VIIRS) instrument, launched in October 2011 on the Suomi National Polar S-NPP, is designed to provide observation continuity with many of the data products from MODIS. As of 2014, however, there are no plans to produce a number of the forest productivity products focused on biophysical attributes such as LAI or NPP/GPP. More work is required to achieve the stated goal of MODIS data continuity through the use of VIIRS [107], thus ensuring it can provide the types and levels of detail required to meet the needs of the vegetation modellers globally.

Direct Estimation of Forest Growth

As discussed in this review, when trying to predict forest productivity, most studies estimate forest "stock" attributes such as volume and biomass rather than "fluxes" like current and mean annual or periodic growth increment. With the accuracy of LiDAR data, it is now possible to refine these approaches to estimate the increment directly; however, few studies have attempted to do so. For example, a number of potential approaches exist including the use of two spatially registered LiDAR datasets acquired at different points in time; LiDAR data acquired at one time step and photogrammetric stereo matching at a second time step are possible. Each of these options comes with different cost and accuracy considerations [57•].

Recently, there has been an increased interest in the generation of canopy-height models from a combination of high spatial resolution digital aerial photography and LiDAR. Semi-Global Matching (SGM) is an approach that can be used to generate high-density point clouds from a stereo pair of digital images [106•]. As a result, the combination of an initial DEM derived from LiDAR data with a second later acquisition of digital photos may be a cost-effective way to derive changes in forest height and is worthy of additional research. It also offers the capacity to utilize historical aerial photography to derive previous growth rates of forest stands. Considerable research is required to determine the appropriate design of repeat LiDAR surveys for measurement of tree height growth [108–110]. Research is also needed to better understand the amount of time needed for sufficient growth to exceed noise and other uncertainties within LiDAR systems, as well as to better understand the impact of growth increment of different species associations, canopy structure, and site conditions on LiDAR change-in-height metrics.

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Compliance with Ethics Guidelines

Conflict of Interest The author declares that he has no competing interests.

Human and Animal Rights and Informed Consent This article contains no studies with human or animal subjects performed by the author.

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- •• Of major importance

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