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Review and synthesis

The role of remote sensing in process-scaling studies of managed forest ecosystems ☆

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ABSTRACT

Sustaining forest resources requires a better understanding of forest ecosystem processes, and how management decisions and climate change may affect these processes in the future. While plot and inventory data provide our most detailed information on forest carbon, energy, and water cycling, applying this understanding to broader spatial and temporal domains requires scaling approaches. Remote sensing provides a powerful resource for "upscaling" process understanding to regional and continental domains. The increased range of available remote sensing modalities, including interferometric radar, lidar, and hyperspectral imagery, allows the retrieval of a broad range of forest attributes. This paper reviews the application of remote sensing for upscaling forest attributes from the plot scale to regional domains, with particular emphasis on how remote sensing products can support parameterization and validation of ecosystem process models. We focus on four key ecological attributes of forests: composition, structure, productivity and evapotranspiration, and disturbance dynamics. For each attribute, we discuss relevant remote sensing technologies, provide examples of their application, and critically evaluate both strengths and challenges associated with their use.

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Contents

1. Introduction 110
2. Remote sensing and scaling approaches 110
3. Forest composition 111
4. Forest structure 112
   4.1. Remote sensing of structure 112
   4.2. Applications 113
5. Forest dynamics and disturbance 114
   5.1. Characteristics of disturbance 114
   5.2. Remote sensing methods for disturbance 115
   5.3. Attributing disturbance events 116
6. Forest productivity and evapotranspiration 117
7. Future directions 118
8. Conclusion 119
   Acknowledgements 119
   References 119

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1. Introduction

Forests provide critical ecosystem services to society, including provision of food and fiber, maintaining water availability and quality, and regulating climate (Krieger, 2001; Millennium Ecosystem Assessment, 2005). Sustaining these services under increasing societal demand depends on effective forest management, which in turn relies on solid scientific understanding of the natural processes of carbon, water, and nutrient cycling. Historically, much of our scientific knowledge on key ecological processes and management impacts has come from field-based studies and experimental manipulations. To extrapolate this understanding to larger domains in both time and space, however, requires scaling techniques often based on forest inventories and ecological modeling. Upscaling plot-level measurements of carbon, water and nutrient cycling in forests to broader spatial and temporal scales can be accomplished by different approaches including measure-and-multiply, or "book-keeping", techniques (e.g., Houghton et al., 1983), formal national-level resource inventories (e.g., Heath et al., 2011), and mechanistic modeling of biogeochemical processes (e.g., Thornton et al., 2009). Across these various scaling approaches are common data requirements for initializing, calibrating, driving and validating these methods.

Remote sensing observations and derived products fill a critical role in meeting these data requirements, particularly where spatially- and temporally-explicit information is needed for inputs and evaluation (Turner et al., 2004). In theory, remote sensing is straightforward. Energy from either the sun or the sensor itself can be interpreted as it interacts with the Earth's surface to infer forest attributes or, as observations are combined over time, change. These inferences can be made over different spatial scales and frequencies, with consistent records going back decades in some cases. From this simple concept however come a large variety of sensors that vary by platform, passive or active systems, spectral wavelengths, spatial resolution and coverage, and repeat frequency and available historical record (Jensen, 2009). The choice of system, or combination of systems, depends on the scale of the application or process of interest and the particular forest attribute of interest (e.g., composition, structure, productivity, water balance, or disturbance).

Here we review current remote sensing capabilities that can be used to characterize carbon, water, and nutrient cycling in managed forests. Our particular focus is describing remote sensing data and products describing key ecosystem attributes that can be used to parameterize process-based models, or scale inventory and field measurements to regional or even global extents. Despite the wide differences across the various scaling approaches, there are common spatio-temporal data requirements that can be addressed by remote sensing. Accordingly, we discuss the application of remote sensing to four key ecological aspects of forests: composition, structure, productivity and evapotranspiration, and disturbance dynamics.

Our emphasis is not exclusively on data sources that directly inform forest management (which often requires spatial resolution at the scale of individual stands), but more broadly on data sources useful for studying the ecological impact of forest management as a land use practice. We also note that the definition of "managed forest" itself is ambiguous, encompassing management goals as diverse as maximizing extraction (rapid rotation harvest, fertilization, thinning) and minimizing disturbance (fire suppression, protection from development). For example, large swaths of forest in the US and Canada are designated as "managed", although their composition and structure do not differ substantially from "natural" forests with similar land use history. Most of the discussion in this paper focuses on extractive management, including clear-cutting, partial harvest, and planting, by which human activities rapidly alter forest attributes. Given the increased societal attention to forest resource pressures and environmental uncertainty, we also discuss emerging challenges and opportunities in the use of remote sensing to inform forest science, management, and policy.

2. Remote sensing and scaling approaches

To support sustainable management of forest resources, we need to understand the broader implications of our local-scale knowledge of ecological processes. Most any scaling approach will first require at least one – or more typically many – geospatial map product(s) describing forest attributes across the landscape of interest. Whether using a simple spreadsheet or "book-keeping" approach (e.g., Houghton, 2003) or more sophisticated process-based simulation modeling (e.g., Melillo et al., 1993), the basic premise of a scaling approach is to associate a particular parameter with the land cover or forest type where it was measured, and then extrapolate its local value according to the areal extent and spatial pattern of that type across the mapped landscape. For example, in their book-keeping approach to estimate the forest-sector greenhouse gas budget of Mexico, de Jong et al. (2010) developed a nation-wide initial biomass estimate by extrapolating measured, per area carbon stock density values to the spatial extent of the main forest cover types based on medium spatial resolution (30 m) satellite data classification. In U.S. forests, higher spatial resolution maps of composition and structural attributes have been achieved using statistical scaling techniques that integrate inventory plot data with optical- and laser-based remote sensing (e.g., Blackard et al., 2008; Ohmann et al., 2014; Zald et al., 2014). At the global-scale, process-based simulations by biogeochemical and land surface models require initialization with maps of plant functional types (PFTs) that are typically based on coarse resolution ($\sim$1 km) remote sensing data products (e.g., Jung et al., 2006; Huntzinger et al., 2013; Wullschleger et al., 2014). Where data products are available at finer scales ($\sim$1 m–30 m), some process-based modeling applications can be directly initialized with spatially-explicit data on forest biomass (e.g., Kimball et al., 2000), structural characterizations (e.g., Hurtt et al., 2004) or foliar chemistry (Ollinger and Smith, 2005) (Fig. 1).

Repeat remote sensing imagery that captures forest dynamics through multiple observations over time is also used to explicitly drive inventory and modeling approaches for quantifying changes in carbon, water and nutrient cycling at landscape to regional scales. While model initialization data incorporate the spatial variability of a particular parameter, remote sensing driver data are used to represent the temporal dynamics of that parameter. In the greenhouse gas accounting example cited above, de Jong et al. (2010) calculated the change in Mexico forest-sector carbon stocks by updating their initial area-based biomass estimate with two time-periods of spatially-explicit land cover change maps classified from Landsat imagery. The national carbon accounting system in Canada is also largely driven by modeling the components of change based in part on remote sensing of forest disturbances, such as wildfires and insect outbreaks (Kurz et al., 2009). Similarly, these components of change can be incorporated into simulation modeling frameworks to capture the impacts of disturbance and land use change on ecosystem processes (e.g., Galford et al., 2010; Hayes et al., 2011; Turner et al., 2011). Remote sensing indices are also used in empirical and explicitly diagnostic scaling approaches, such as the global estimation of vegetation productivity based on the light-use efficiency (LUE) approach (Running et al., 2004) and the upscaling of site-level observations of carbon, water

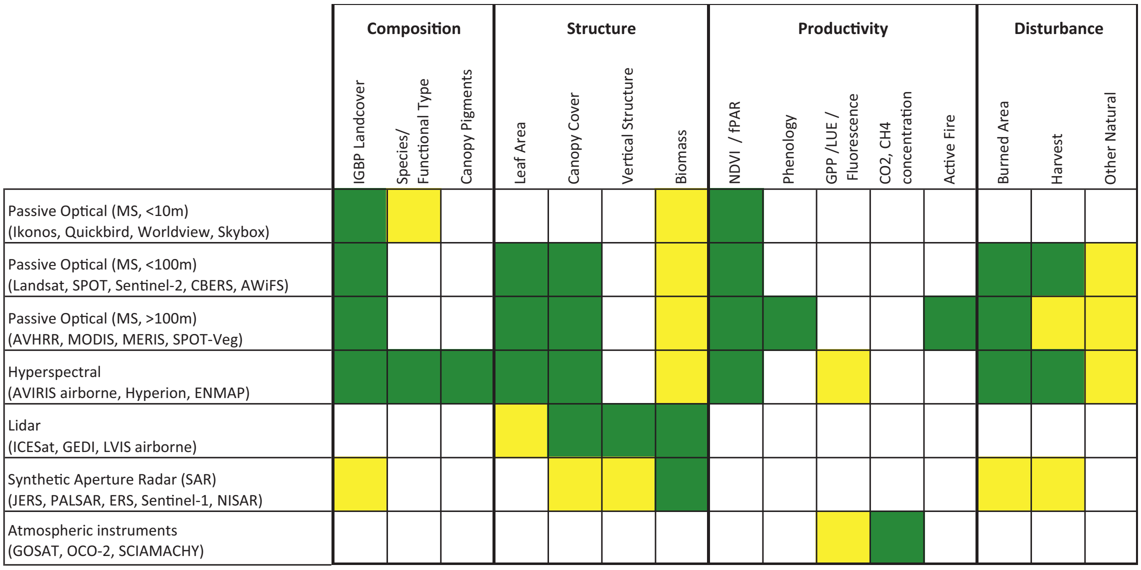

Fig. 1. Key variables needed to scale ecosystem studies or parameterize process models, and the relevant remote sensing approaches for their retrieval. Remote sensing modalities (passive optical, radar, etc.) are shown in the left column together with common sensor examples. Green = modality is strongly relevant for retrieving variable; yellow = modality can support variable retrieval, subject to limitations in accuracy. Note that additional geographic and temporal limitations may limit application (e.g. the lack of a global hyperspectral system limits the ability to retrieve canopy pigments globally, despite the relevance of the technology). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

and energy fluxes based on eddy-covariance techniques (Jung et al., 2011). There are also many examples of numerical modeling frameworks that directly incorporate satellite-derived productivity indices as key drivers in diagnostic simulations of ecosystem processes (e.g., Potter et al., 1993; Coops and Waring, 2001; Turner et al., 2006a,b).

A final data requirement for ecosystem scaling approaches is a set of known target values to both calibrate and validate the empirical or numerical simulation model. These cal/val data are often subsets of the same type and source, and historically have primarily come from plot-based measurements. These site-level data can be used to parameterize and verify ecosystem process models for particular forest types (e.g., Medvigy et al., 2009; Richardson et al., 2010), but available data are limited in both space and time. To capture broader spatio-temporal variability in model evaluation, studies of forest carbon, water and energy exchange have made use of regional-scale networks of eddy-covariance towers (Fisher et al., 2008; Schaefer et al., 2012). Still, the spatially and temporally limited observations from these networks can under-represent important forest regions and associated ecological processes (Hargrove et al., 2003; Hayes and Turner, 2012). Remote sensing data have the potential to provide spatially and temporally explicit, consistent and comprehensive benchmarks for model evaluation (Luo et al., 2012; Mao et al., 2012a,b). Remote sensing data can also be directly assimilated into process-based models as a constraint on system dynamics (e.g., Luo et al., 2011; Quaife et al., 2008; Rayner et al., 2005).

The various scaling approaches each offer advantages and disadvantages depending on the science or management question being addressed. Because each approach might focus on a different aspect of carbon, water and nutrient cycling, the choice of approach is important and any cross-evaluations must be careful to consider "apples-to-apples" comparisons (Hayes and Turner, 2012). Although there are benefits in retaining independence for such comparisons, progress can also be made in scaling questions by considering multiple constraints (Hayes et al., 2012) as well as more formally integrating across approaches (Turner et al., 2013). Remote sensing can serve as a key integrator in this effort, where opportunities exist to use repeat coverage, spatially-explicit data to calibrate, initialize, drive and validate both inventory and modeling approaches to scaling forest ecosystem processes. Along with these opportunities, however, come significant challenges with the use of remote sensing in managed forests. There are methodological limitations and various sources of error in remote sensing data themselves that need to be overcome. In most cases, it is not possible to remotely sense the ecological process of interest directly, and thus to produce the desired output some level of model (which itself needs calibration and validation) is required. At the foundational level, though, remote sensing data and methods have demonstrated the ability to inform scaling studies of ecological processes by characterizing their underlying indicators. Here, we review the state-of-the-art in remote sensing of these indicators in managed forests, namely composition, structure, productivity and evapotranspiration, and disturbance dynamics, and discuss the opportunities and challenges going forward for this important field of research.

3. Forest composition

To accurately represent ecological processes, models require some depiction of vegetation composition. Typically, models parameterize rate constants (e.g. mortality, carbon allocation, plant-atmosphere fluxes) by assigning values based on vegetation type (e.g. Hudiburg et al., 2009). Historically, vegetation type was assigned at coarse resolution using fixed land cover classes based on climate regimes or field observations (Matthews, 1983). With the advent of reprocessed global AVHRR satellite data in the mid-1980s, researchers began to construct global land cover representations at finer scales, and with additional information derived from seasonal observations of vegetation greenness (Tucker et al., 1985; Justice et al., 1985; Loveland et al., 2000). Remote sensing classification schemes for land cover have typically relied on stratification among a few key structural and functional variables, including leaf type (needle, broadleaf), leaf longevity (deciduous, evergreen), stem structure (herbaceous vs. woody), and stature (shrub vs. treed). Biogeochemical and ecological models have been parameterized using global land cover maps derived from AVHRR, MODIS, and SPOT-Vegetation (Jung et al., 2006; see also references in Section 5), ranging in spatial resolution from 500 m to 8 km, although other models specify vegetation types internally in response to local edaphic conditions, climate, and competitive dynamics (Quillet et al., 2010).

For global models operating at 1/4 to 1 degree, a challenge has been to adequately represent the heterogeneity of land cover classes within a single grid cell. In many cases models simply adopt the most common, or modal, land cover type to represent the entire cell. However this practice tends to underestimate the biophysical impacts of small, disaggregated land cover types such as urban areas, small-scale agriculture, wetlands, and riparian forests. More sophisticated parameterizations incorporate observed mixtures of land cover within each cell, essentially running separate model simulations for each land cover fraction, and then aggregating the component fluxes and stocks (Koster and Suarez, 1992; Bounoua et al., 2006; Melton and Arora, 2014) or tracking them as individual but not spatially-explicit "cohorts" (Hayes et al., 2011).

Identifying managed forests as a specific class often requires combining information on both composition and temporal dynamics. Large plantation monocultures, such as oil palm and eucalyptus have been successfully mapped using MODIS time series data. In the case of Eucalyptus, short-rotations (6–7 years) provide a diagnostic NDVI signature (le Maire et al., 2014; Marsden et al., 2010). Oil palm has been mapped via diagnostic phenology compared to surrounding forest (Gutiérrez-Vélez and DeFries, 2013), as well as visual interpretation of high-resolution data (Thenkabail et al., 2004) and application of traditional classification approaches to radar and optical data (Santos and Messina, 2008). In other cases, identifying managed forests relies less on unique phenology or spectral signatures, and more on the relative level of disturbance activity compared to "natural forests". For example, the prevalence of stand-clearing disturbance in the southern United States is readily ascribed to pine forestry across much of the region (Masek et al., 2008; Hansen et al., 2010). In regions with less intensive management practices, including selective harvest and partial harvest, it may be difficult to separate the temporal signature of management from natural disturbances such as storm damage and insect mortality (Thomas et al., 2011).

The use of remote sensing derived land cover within ecological models is by now well established, and recent attention within the remote sensing community has focused on creating more ecologically relevant descriptions of composition. In particular, the concept of mapping vegetation functional types, rather than land cover types, has gained currency. While the precise definition of functional type has been debated (Gitay and Noble, 1997), the term refers to plant communities that either share a common ecosystem function, or share a common response to a perturbation such as disturbance or stress. In theory a landscape unit can have multiple descriptions incorporating function, response to stress, structure, and temporal behavior. Thus, rather than simply stratifying vegetation into fixed classes, a given patch could (for example) fix nitrogen, feature serotinous reproductive strategies, and be a woody perennial.

Derivation of functional types has commonly centered on the use of fine spectral resolution (hyperspectral) data in order to discriminate among different plant attributes. Physically, the use of hyperspectral data allows retrieval of specific biochemical compounds associated with plant function and structure, including foliar nitrogen, C/N ratios, chlorophyll concentration, and structural compounds (lignin, cellulose) (Kokaly et al., 2009; Ustin et al., 2009). Numerous studies have used hyperspectral imagery to map specific plant communities (Roberts et al., 1998; Clark et al., 2005) and functional traits (e.g. Asner and Vitousek, 2005; Asner et al., 2015). However, reliably translating leaf-level reflectance spectra to the canopy scale remains challenging. While foliar chemistry and structure control leaf-level spectra, canopy spectra are strongly affected by forest structure (eg. leaf-area, branch area, shadowing), compositional mixing among multiple species, and non-vegetated components such as soil visible through canopy gaps (Asner, 2008). Thus care must be taken to consider the role of canopy structure as well as leaf biochemistry in interpreting observed reflectance spectra (e.g. Knyazikhin et al., 2013). In addition, there are currently no operational hyperspectral observatories in orbit that provide routine global coverage. Limited data have been collected by the EO-1 Hyperion sensor since 2000, and new data are planned from the German EnMAP satellite beginning in 2018.

4. Forest structure

Forest structure refers to the three-dimensional organization of individual trees on the landscape, as well as the way that canopy elements fill space. Specific structural attributes derived from remote sensing include stand height, stem density, fractional canopy cover, canopy vertical distribution, and biomass. Knowledge of forest structure is critical for ecosystem modeling for several reasons. First, structural elements such as height and stem density are directly related to above-ground biomass and thus carbon storage (Hall et al., 2011). Ecosystem models can use observed biomass data to constrain productivity and wood turnover so that, for example, potential biomass within the model does not exceed maximum observed biomass (Williams et al., 2012, 2014). In addition, models that explicitly include size or age cohorts benefit from knowing the distribution of tree sizes within a model grid cell. For example the Ecosystem Demography (ED) model accounts for the growth and aging of individual trees, and can adjust aggregate productivity based on observed height distributions (Hurtt et al., 2004; Thomas et al., 2008; Antonarakis et al., 2011). Finally, at the scale of individual trees, the distribution of leaf area and canopy gaps controls the radiation balance at various levels within the canopy. In principle such information could be used to drive explicit models of photosynthesis within the canopy, although to date most models do not approach that level of detail (Loew et al., 2014).

4.1. Remote sensing of structure

A variety of remote sensing technologies have been used to retrieve vegetation structural attributes (Fig. 1). Passive optical techniques rely on reflected solar radiance to provide information. Active techniques probe vegetation canopies using energy emitted from the remote sensing platform itself, and include radar and lidar approaches.

Passive optical methods have been used for over four decades to retrieve vegetation structure and biomass, but have met with inconsistent results (Lu, 2006; Powell et al., 2010). Canopy reflectance tends to be dominated in the visible and near-infrared by the outer layer of the canopy foliage. In the visible wavelengths, too little light passes through the leaves to probe deeper structural levels, while in the near-infrared multiple scattering among leaves leads to an asymptotic saturation of the signal regardless of structure (Asner, 1998). As a result, there is little information provided on vertical structure in closed canopy forests. However, passive optical data are sensitive to the spatial arrangement of shadowing and "background" (e.g. soil, litter) exposure across the landscape. Passive optical data are thus useful for determining canopy cover, and, in sparse forests where cast shadows are diagnostic of tree heights, passive optical data have been used to retrieve biomass with relatively high accuracy (Cohen and Spies, 1992; Hall et al., 2006). In addition, for younger stands where both height and reflectance are changing rapidly, time series analysis of reflectance

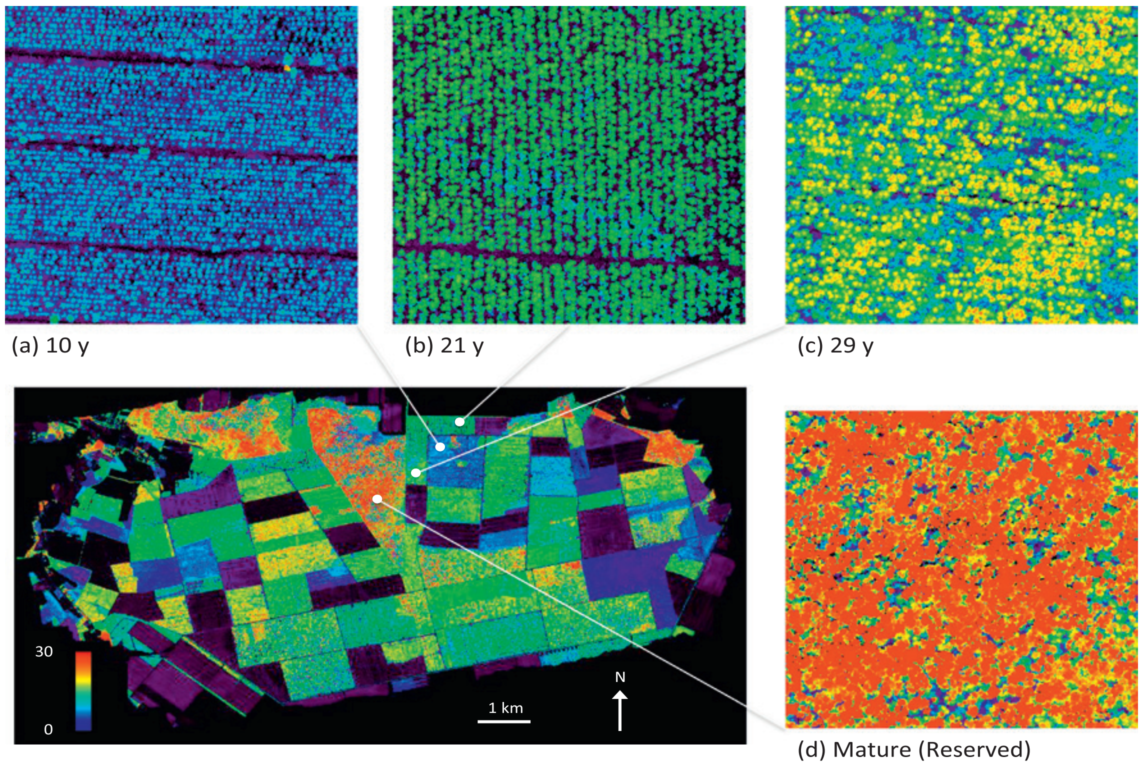

Fig. 2. Example of airborne lidar canopy height measurements from the Parker Tract, North Carolina, using the NASA Goddard's Lidar, Hyperspectral, and Thermal (G-LiHT) instrument package (Cook et al., 2013). The site consists of a mosaic of planted loblolly pine with known stand age (a–c), as well as patches of older, unmanaged forest (d). Indications of management practice (row planting, strip thinning) are visible in the insets a–c.

trajectories have been successfully correlated with current-year biomass (Pflugmacher et al., 2012).

Radar and lidar methods tend to perform better than passive optical methods in higher biomass, closed canopy forests (Zolkos et al., 2013). Radar backscatter using longer wavelengths (e.g. L-band, P-band) provides penetration of the canopy branch structure, but tends to saturate at biomass levels higher than ~100 Mg ha^{-1} AGB (Imhoff, 1995). More recent studies have used radar interferometry (based on converting the phase shift between spatially separated radar signals to calculate distance to the receiver) to characterize the surface and the interior "topography" of canopies (Treuhaft et al., 2004). Interferometric techniques have been shown to be sensitive to biomass up to 300–400 Mg ha^{-1} AGB for X- and P-band (Treuhaft et al., 2015; Minh et al., 2014). Current or upcoming radar missions include the Japanese PALSAR-2 (L-band), the European Sentinel-1 mission (C-band), the European BIOMASS mission (P-band, to be launched in 2020), and the US/Indian NISAR (S- and L-band, to be launched in 2020).

Lidar is often considered to be the optimal remote sensing approach for retrieving structural attributes in higher biomass forests where other methods saturate, since it provides a direct measure of both the vertical and spatial distribution of canopy elements. In particular, lidar can directly measure stand height, which correlates strongly with biomass (Hall et al., 2011). Discrete return lidar systems collect the timing of the first (or first and last) reflected pulse (Lim et al., 2003). Airborne discrete returns often provide very dense sampling, with detection of up to 20 returns per square meter, generating point clouds that visually depict individual tree crowns, terrain, and understory (Fig. 2). As noted below, such information can be used to parameterize individual-based ecosystem models (Hurtt et al., 2004; Thomas et al., 2008; Antonarakis et al., 2011). Waveform lidar systems collect the full distribution of reflected energy from the canopy, essentially providing a vertical profile of the canopy density (Lim et al., 2003). Various studies have reported success in retrieving biomass levels of up to 300–400 Mg ha^{-1} using full-return lidar, although site characteristics (including species composition and local topography) may reduce retrieval accuracy (Ahmed et al., 2013).

4.2. Applications

With the increase in satellite-based radar and lidar systems (e.g. ICESat GLAS, ALOS PALSAR), a number of recent studies have used remote sensing observations in conjunction with field data to create map-based estimates of above-ground biomass for the pan-tropics (Saatchi et al., 2011; Baccini et al., 2012), the United States (Kellndorfer et al., 2004); and the circum-Arctic (Neigh et al., 2013). These efforts have typically used multiple remote sensing inputs, and statistical modeling techniques to "train" regression models based on available field data, and provide map estimates with spatial resolution of 30 m to 1 km. The high uncertainty associated with these products (often 20–40%) reflects limitations in the amount of field-measured biomass available across the globe, as well as limitations in current radar and lidar datasets. For example, although ICESat GLAS has been used in many recent studies, its spatial resolution (~60–80 m) is not optimal for measuring vegetation structure in complex terrain. When implemented on the International Space Station (ISS) in 2018, the NASA Global Ecosystem Dynamics Investigation (GEDI) vegetation lidar should improve the quality of biomass datasets by providing denser laser sampling, as well as finer spatial resolution (20 m) for each laser spot. Due to the ISS orbit, only land areas between 52 degrees north and south will be mapped during the GEDI mission.

One complication, however, is that traditional modes of inference do not easily support uncertainty analysis of forest population parameters derived by simply adding up modeled pixel values. This is evident, for example, when the ecoregion-level biomass values implied by alternative maps do not intersect each other's confidence intervals (Mitchard et al., 2014). There are, however, straightforward ways to integrate lidar measurements as discrete observations in a formal sample/survey framework (Wulder et al., 2012), an approach which has been pursued using both airborne (Ståhl et al., 2010) and spaceborne (Healey et al., 2012) lidar data. GEDI will likely incorporate these principles in order to improve population estimates. The improved sampling density of GEDI should allow biomass estimates with <20% absolute error within cells finer than 25 ha, a scale approaching that at which individual forest tracts may be managed.

A number of studies have successfully used active remote sensing to retrieve structural attributes in managed and disturbed forests, and to distinguish structural differences associated with forest extraction. Dolan et al. (2011) found a significant change in regional stand height before and after Hurricane Katrina using ICESat GLAS data. Similarly, Margono et al. (2012) found a statistically significant difference in GLAS-derived canopy height between primary intact and primary degraded forests in Indonesia. Ryan et al. (2012) used three-years of L-band radar from ALOS PALSAR to identify changes in carbon stocks in degraded Mozambique woodland as small as 12 Mg ha^{-1} with 95% confidence. These results indicate the potential of active remote sensing to quantify specific levels of forest extraction or degradation apart from simply stand clearing events such as clearcutting. An innovative study by d'Oliveira et al. (2012) used airborne lidar to identify subcanopy logging roads and skid trails in a degraded section of Amazonian forest (Brazil). A key finding was the ability of lidar to map specific management practices that would otherwise be hidden by the overstory canopy.

In addition to characterizing the current state of forests, active remote sensing can be used to monitor long-term changes in structure. The most direct approach is to use the same instrumentation to acquire repeated lidar or radar datasets over a period of years. Particularly in the case of lidar, there have been relatively few experiments of this nature to date. Dubayah et al. (2010) used repeated measurements from the LVIS airborne lidar system over La Selva, Costa Rica to map height and biomass change between 1998 and 2005. In addition to recording losses due to clearing and disturbance, they were able to identify areas of increasing height and biomass within growing, secondary forests. Similarly, Rosette et al. (2015) used repeated measurements from LVIS (2009–2013) to identify structural changes associated with forest management in Howland, Maine. Since comparable, repeat-pass lidar datasets remain rare, a number of studies have combined one-time structure information from lidar with disturbance history from passive optical sensors such as Landsat or MODIS. For secondary forests, knowing the time since clearing (from historic Landsat imagery) and current biomass from lidar, the mean rate of biomass accumulation across a region may be obtained (Helmer et al., 2009; Dolan et al., 2009).

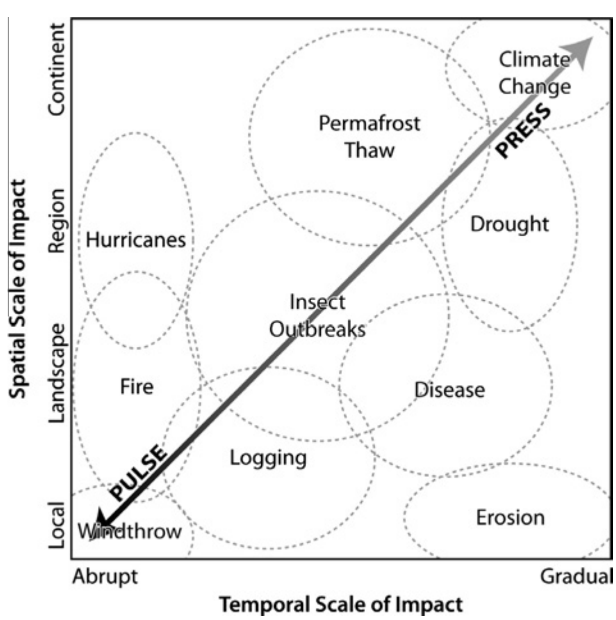

Fig. 3. Anthropogenic and natural disturbances can be characterized across a press–pulse spectrum in terms of the spatial and temporal scale of their impact on managed forests. The choice of the spatial and temporal scale of remote sensing data used to detect and characterize different disturbance types varies with these press–pulse characteristics.

5. Forest dynamics and disturbance

Disturbance processes that result in tree growth decline and/or mortality are a ubiquitous and constant feature of managed forest landscapes (Fig. 3). Disturbances can be caused by natural processes such as wildfires, insects and disease, and wind-throw and storm events, or from anthropogenic processes such as logging, pollution, deforestation, and the introduction of invasive species. The broader landscape patterns of forest composition, structure and function are a reflection of the regional disturbance regime, defined by the dominant type, extent and frequency of disturbance. Superimposed on climate and landscape characteristics, disturbance is a key determinant of forest heterogeneity at regional scales (Sousa, 1984).

Disturbance events change the composition and structure of the forest, alter carbon, water and nutrient cycling, and reset successional processes (Goward et al., 2008; Williams et al., 2014; Hicke et al., 2012; Chambers et al., 2007). The impacts of disturbance on forests are both direct, as with short-term tree mortality and the mass transfer of carbon, and indirect through modifying the physical environment that influences longer-term successional trajectories of carbon, water and nutrient cycling (Kasischke et al., 2013). At the local-scale, the amount and nature of mortality, carbon transfers and physical impacts are all dependent on the type and severity of disturbance (Keeley, 2009; Goetz et al., 2012). The broader-scale impacts over time and space depend on the frequency and extent of disturbances over larger areas. Characterization and quantification of these key attributes of forest disturbances (i.e., type, severity, frequency and extent) are required for estimating or simulating the ecological impacts of forest disturbances in scaling frameworks and process models (Liu et al., 2011).

Here we review and discuss the opportunities and challenges in employing different remote sensing technologies and methods for creating the disturbance data products needed for informing process scaling studies in managed forest ecosystems. Although there are many different definitions of disturbance (Sousa, 1984; Scheffer et al., 2002; Godron and Forman, 1983; Pickett and White, 1985; Bender et al., 1984), we define forest disturbance here as those processes, both anthropogenic and natural, that result in a loss of forest biomass and redistribution of carbon within the ecosystem. Conversely, those processes that result in post-disturbance changes in vegetation growth we refer to as "regeneration", which should be contrasted with "recovery" in that it does not imply a return to the initial state.

5.1. Characteristics of disturbance

Individual disturbance events can be described by parameters representing cause (or "agent"), spatial extent, severity, duration, and selectivity. In general, the range of disturbance types can be categorized according to more localized and immediate *pulse disturbances* causing abrupt change versus *press disturbances* that result in more gradual impacts over broader areas and longer periods of time (Fig. 3). The choice (and effectiveness) of particular remote sensing data and techniques to detect and characterize different disturbance types varies with these press–pulse characteristics.

Disturbance events with small spatial extents, relative to the spatial grain of remotely-sensed imagery, are substantially more difficult to reliably discriminate from noise than larger events. For example, when using satellite imagery with a 30 m resolution, detection of a large harvest unit is a straightforward detection task whereas identifying tree-fall gaps would require higher resolution imagery with a spatial grain of a few meters. Stand clearing events such as clear-cuts, land-use conversion, and severe fires generate strong signals that can easily be detected through optical remote sensing, whereas subtle changes from nutrient deposition, drought stress, or thinning can be difficult to differentiate from phenological differences or errors in surface-reflectance corrections, particularly if they are over large areas on the order of kilometers and have with indistinct borders.

In addition to varying in size and severity, events can vary in the species-selectivity of the agent (Frolking et al., 2009). The hemlock wooly adelgid, for example, is a species-specific invasive insect that attacks and kills only Eastern hemlocks (Orwig et al., 2012), whereas the Asian gypsy moth is a generalist parasitoid that affects many deciduous species (Townsend et al., 2012). Additionally, wildfires can affect a range of individuals with varying impacts depending on species and size (Garren, 1943). Species-selective harvesting, as opposed to simply choosing mature trees or clear-cutting, can have similar effects. Though species-selective disturbances always have the same detection challenges as low-severity disturbance, they introduce the additional issue of tracking a shifting spectral signal as forest species-composition shifts. Similarly, other disturbances which leave a mostly intact overstory canopy, such as understory fires or harvest, controlled burns, and construction of narrow roadways ($<\sim$6 m), pose detection problems for spectral sensors (Peres et al., 2006).; lidar-derived structural information is useful for identifying these types of events (Azizi et al., 2014).

Finally, both pulse and press disturbance events require appropriate techniques for detection. Pulse disturbances may go undetected if the spectral signal returns to pre-disturbance values within span of the detection technique's temporal window though Townsend's (2012) method for quantifying Gypsy Moth defoliation in the Eastern United states was broadly successful, with a single fixed-effects model producing a mean absolute error of 10.8% defoliation from a cross-validated sample. Conversely, remote sensing methods to detect press events, such as from progressive insect and disease outbreaks, remains challenging since many algorithms are based around the concept of detecting discrete events, rather than long-term decline (Holmgren and Thuresson, 1998; Goodwin et al., 2008; Frolking et al., 2009; Oumar and Mutanga, 2011).

5.2. Remote sensing methods for disturbance

Remote sensing methods to characterize forest disturbance typically rely on first deriving a spectral signature of vegetation through which changes can be detected. A commonly used signature, the normalized difference vegetation index (NDVI, Tucker, 1979), subtracts the red reflectance from near-infrared reflectance to exploit the 'red cliff' in the chlorophyll absorption spectra and thereby estimate chlorophyll concentration. Other common signatures include the normalized burn ratio (NBR, van Wagtendonk et al., 2004), which is used to detect wildfire disturbance (Eidenshink et al., 2007), and the normalized difference moisture index (NDMI), which has been shown to better correlate with biomass by also capturing information about forest canopy shadowing and structure (Wilson and Sader, 2002).

The satellite imagery products most suitable for monitoring managed forest disturbances are constrained by those that are continually acquired, rather than tasked, and are openly available to the public at low- (or no) cost. As such, for forest monitoring purposes, the most common datasets used are those generated from the MODIS sensors onboard the Aqua and Terra satellites (Justice et al., 2002) and the sensors aboard the Landsat family of satellites (Vogelmann et al., 2009). MODIS imagery is available since 2000, and new views are acquired every one to two days. NDVI products can be generated at 250 m resolution from MODIS imagery, though other spectral bands are sampled at coarser resolution. Though the large spatial grain can subsume smaller managed forest plots, the high temporal resolution facilitates continuous monitoring, thereby alerting managers of potential problems that can be spatially pinpointed by other means. Landsat Thematic Mapper data at 30 m resolution are available since 1982, with an opportunity for new acquisitions every 16 days for each satellite; though, due to data constraints, a new image is not acquired at every opportunity. Additionally, the Multispectral Scanner (MSS) instrument aboard early Landsat satellites can extend views back to 1972, though at a resampled spatial resolution of 60 m, a 4-band spectral resolution, and an 18-day return time for Landsat 1 through 3. Despite its potential, though, only a few disturbance detection applications have utilized this legacy Landsat data (e.g. Healey et al., 2008) because its use in time series analysis currently requires significant additional radiometric and geometric processing beyond standard archived formats. In the future, the European Global Monitoring for Environment and Security (GMES) Sentinel-2 mission promises to provide free and open 10–60 m resolution imagery every imagery every-five days at the equator by using two satellites, with orbit characteristics that complement connecting data with observations from SPOT and Landsat (Drusch et al., 2012), thereby gaining some of the temporal advantages of MODIS at much higher spatial resolution.

Early methods to detect forest disturbance from remotely sensed imagery would typically compare two images representing vegetation acquired on two different dates with the difference between the images expressing change (Hayes and Sader, 2001; Garcia-Haro et al., 2001; Masek et al., 2008). Most often, these would be acquired before and after known disturbance events to assess the extent and magnitude of the event of interest (Chambers et al., 2007; White et al., 1996; Wimberly and Reilly, 2007). Like other methods, the magnitude of the spectral change correlates with the disturbance severity.

To a large extent two- or three-date comparisons to find forest disturbance were necessitated by the expense of individual Landsat scenes. With open access to the archive since 2008, methods that incorporate much more data have become popular (Vogelmann et al., 2009) (Fig. 4). These methods can provide both the location and times of disturbance events to create historical baselines of disturbed areas or for ongoing monitoring. The Vegetation Change Tracker (VCT) finds disturbances by detecting deviations in the vegetation index time-series and labeling these years as disturbed (Huang et al., 2010). LandTrendr (Kennedy et al., 2007) finds disturbances by fitting a piecewise linear trend to the vegetation index time-series and then labels segments with negative slope as disturbances. Both of these methods use Landsat imagery and generate a single clear-sky composite image for each year which is then used to detect change. To increase temporal resolution, the methods of Zhu and Woodcock (2012), utilize all available Landsat data to model and remove phenology.

To increase temporal resolution even further, one approach is to combine daily observations from MODIS with higher-resolution

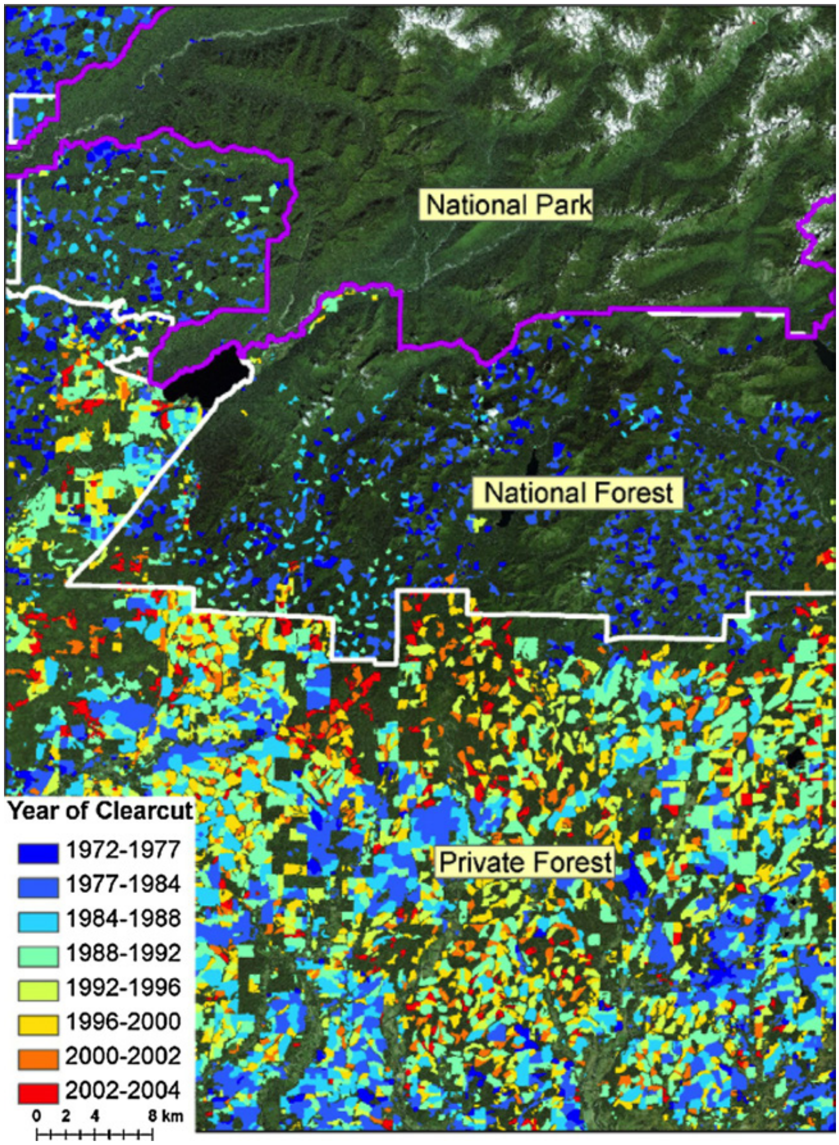

Fig. 4. Disturbances shape all landscapes, and human activity can cause significant differences in forest structure and composition across ownership boundaries. Time series of Landsat imagery are useful for identifying the cumulative impact of human activity; Landsat was used to map clearcut harvests over three ownership classes on the Olympic Peninsula, Washington.

observations from Landsat (e.g. Hilker et al., 2009). The opening of the archive has also facilitated studies with very large spatial extents, such as the mapping of the entire globe from 2000 to 2012 using Landsat data and the Google Earth Engine performed by Hansen et al. (2013). Using only MODIS data, the ForWarn system groups phenological patterns into a set of clusters and then uses deviations from the expected pattern to detect forest change in with delays measured in weeks or days. These techniques have shown promise in both the western United States and in more species-rich Eastern United States forests (Hargrove et al., 2009).

5.3. Attributing disturbance events

While attribution of disturbance type is critical for inclusion of remotely sensed change data in models of carbon dynamics (Zhang et al., 2012) and current and future climate change impacts (Ayres and Lombardero, 2000; Dale et al., 2001), most disturbance maps do not specify type. A major hurdle to creating effective and reliable attribution algorithms is the availability of high-quality training data that labels known individual disturbances with a causal agent. In most studies, the researchers themselves generate these data.

Work by Schroeder et al. (2011) in the Canadian boreal forest used Landsat imagery to distinguish between forest fires and clearcuts that were manually identified by analysts. Although limited to a relatively small spatial area, agent separation rates of 93% were achieved. The shortwave infrared bands contained the most reliable information and imagery acquired soon after the disturbance event was the most effective, though separation could still be achieved with imagery acquired up to four years after the event. Working over the entire Canadian boreal forest, Guindon et al. (2014) used MODIS imagery to separate disturbances caused by fires, harvest, and floods. Using a decision tree model, separation accuracies between 80% and 85% over the entire area were achieved. Smaller and less-serve disturbances, though, were frequently omitted (up to 50%), and the presence of other disturbance agents, such as insect outbreaks, emphasizes the complexity of the attribution problem. Baumann et al. (2014) explored the separation of anthropogenic harvest and natural windfalls using a support vector machine classification approach over spectral information in Russian temperate forests and boreal forests of the United States. The approach generated high classification reliability when a disturbance was detected, but omitted many disturbance events less than approximately 5 ha in area. These approaches based on generating individual training data sets can be inefficient as similar work is repeated and the comparability of methods is limited since the set of disturbances detected and labeled differs between studies. The human interpretation aspect of this approach can create bias since the same researchers generate both the training data and the detection/classification tool.

Using information from the remote sensing imagery other than just pixel-by-pixel spectral values may increase classification accuracy. Using a neural network approach over spectral information and information about spatial variability and using known disturbance extents from the US Forest Service's Aerial Detection Survey (McConnel et al., 2000), eight difference disturbances were separated in temperate forests in the eastern United States, including insect pests and diseases. Classification accuracies ranged from 42% to 90% for different agents, with reliabilities following a similar range and performance matching the quantity of high-quality data available for training the classifier (Hughes, 2014). Visual examination of forest disturbance events can often reveal if the cause is harvest or some natural disturbance by the regularity of the disturbance event. This follows the more general observation that more regular landscapes are more heavily human-impacted (O'Neill et al., 1988). Classification using the shape and regularity of disturbance patches is a promising approach to differentiating between anthropogenic and natural disturbances (Antonova et al., 2013).

6. Forest productivity and evapotranspiration

Forest net primary production is an ecosystem service in the context of both providing wood and driving carbon sequestration. Net primary production (NPP) is the rate of carbon uptake by vegetation, which is the balance between photosynthesis, or gross primary production, and autotrophic respiration (Chapin et al., 2006). Carbon sequestration considers stocks and fluxes in additional ecosystem components (e.g., soils, wood products, aquatic systems, and disturbances) and is determined as the longer-term net ecosystem exchange (NEE) or net ecosystem carbon balance (NECB). Remote sensing has been applied to scaling forest productivity and carbon budget estimation for monitoring purposes using a range of approaches. Wood production can be mapped most simply with statistical techniques that combine remote sensing data (e.g. Landsat), and other spatially distributed datasets such as climate reanalysis, with forest inventory measurements (Ohmann and Gregory, 2002; Ohmann et al., 2012). For more process-based approaches, a numerical model with algorithms for simulating some level of mechanistic detail in factors controlling vegetation and/or ecosystem production is employed.

Process-based simulation models come in several varieties (Table 1) that differ significantly in organizing structure (Huntzinger et al., 2013; Fisher et al., 2014), which determines their data input requirements. With respect to simulating NPP, process models are broadly categorized into diagnostic-formulations, in which some variant of leaf area index is prescribed by remote sensing, and prognostic formulations, which simulate their own leaf biomass dynamics (Huntzinger et al., 2012). This categorization is also a fundamental determinant for whether and how remote sensing data are used in the modeling framework. Diagnostic models typically calculate photosynthesis based on a light use efficiency (LUE) approach (Landsberg and Waring, 1997), which is driven directly by remotely sensed measurement of absorbed photosynthetically active radiation (APAR). Prognostic models, on the other hand, simulate primary productivity internally via biochemical algorithms representing carbon assimilation or more detailed enzyme kinetics (Farquhar et al., 1980).

A key observation underlying the light use efficiency scaling algorithm is that NPP (gC m^{-2} $year^{-1}$) is generally correlated with APAR (MJ m^{-2}). Hence, LUE can be determined in terms of gC MJ^{-1} and NPP estimated from APAR. It is gross primary production (GPP), as estimated from measurements of net ecosystem exchange at an eddy covariance flux tower (Waring et al., 1995), which is most closely related to APAR, so LUE is often expressed in terms of GPP at a daily time step. Autotrophic respiration (subtracted from GPP to get NPP) is commonly evaluated as a vegetation type specific proportion of GPP (e.g. King et al., 2011).

Remote sensing contributes to the determination of APAR by providing an estimate of the fraction of PAR (FPAR) that is absorbed by the vegetation canopy (Gower et al., 1999). Empirical relationships of measured FPAR (or leaf area index) and spectral vegetation indices, as well as radiation transfer theory, have been used to map spatial and temporal patterns in FPAR (Myneni et al., 2002). Global and regional fields for daily solar radiation and meteorological variables are now available from reanalysis data (e.g. Zhang et al., 2007).

The simplest elaboration of the LUE scaling approach is to determine a maximum LUE from flux tower observations and reduce it for stress factors related to environmental drivers such as minimum air temperature and vapor pressure deficit. This LUE approach has been applied globally using both AVHRR (Nemani et al., 2003) and MODIS (Zhao and Running, 2010) imagery. Validation studies at networks of eddy covariance flux tower sites have helped evaluate and improve the MODIS-based GPP/NPP algorithm (Turner et al., 2006a,b; Heinsch et al., 2006). Applications have included attempts to estimate the proportion of global primary production that is appropriated for human use (Milesi et al., 2005).

Besides FPAR, remote sensing can potentially provide additional information relevant to the LUE scaling approach. Several spectral

Table 1
Examples of different formulations of process-based models and how remote sensing data is used in simulating forest and ecosystem productivity. The examples shown here are taken from models participating in North American Carbon Program synthesis and inter-comparison activities (Huntzinger et al., 2012, 2013). Photosynthetic formulation is categorized by either enzyme kinetic (EK) or light use efficiency (LUE).

Model	Photosynth. formulation	Vegetation distribution	Phenology	Leaf area index	Fire	Land use change	Reference
CASA GFEDv2	LUE	MODIS	GIMMS NDVI	Assimilated from remote sensing	Prescribed (MODIS)	None	van der Werf et al. (2004)
CLM4	EK	MODIS	Prognostic	Dynamically calculated	Prognostic	Modeled	Thornton et al. (2009)
ISAM	LUE	AVHRR	N/A	Assimilated from remote sensing	Implicit	Modeled	Jain and Yang (2005)
TEM6	EK	AVHRR	Prognostic	Dynamically calculated	Prescribed (various RS products)	Modeled	Hayes et al. (2011)
VEGAS2	LUE	Dynamic	Prognostic	Dynamically calculated	Prognostic	Modeled	Zeng et al. (2005)

vegetation indices have been correlated with LUE in forest ecosystems (e.g. Nakaji et al., 2008). In addition, leaf-scale (and to a lesser degree canopy-scale) observations suggest subtle shifts in the proportions of different photosynthesis-related pigments that are detectable by way of changes in reflectance of specific wave bands (Garbulsky et al., 2011). These features are best observed with a high spectral resolution spectroradiometer such as AVRIS, but are also potentially captured with MODIS wave bands (Goerner et al., 2011). Alternatively, there is a signal associated with photosynthesis-driven chlorophyll fluorescence (Parazoo et al., 2014) which is retrievable from space-borne sensors such as GOSAT and OCO-2. The application of these advanced approaches has just begun and their operational use will require a large calibration and validation effort (Grace et al., 2007).

While NPP simulation by prognostic models is not driven directly by remote sensing data, both categories of models make use of derived products from remote sensing (e.g., plant functional type maps) for initialization, parameterization, extrapolation and evaluation of productivity and carbon cycle indicator estimates (e.g., Huntzinger et al., 2013). In some cases, prognostic models 'predict' spectral indices such as the normalized difference vegetation index that can be directly compared with satellite data (Mao et al., 2012a,b). Prognostic productivity models that employ an enzyme kinetics photosynthesis algorithm also commonly simulate a full carbon balance (e.g. Thornton et al., 2002). Notably, heterotrophic respiration (which returns carbon to the atmosphere) must be accounted for in tracking carbon sequestration using a flux simulation approach. Other important fluxes potentially informed by the combination of remote sensing data and process models include thinning/harvesting removals (Turner et al., 2011) and wildfire emissions (Meigs et al., 2011). Potentially, all the information that is beginning to emerge (from multi-temporal Landsat data, for example) on disturbance timing, attribution, and magnitude can be input to an appropriately designed process model to simulate carbon cycle impacts (e.g. Thornton et al., 2002).

The combination of ground-based observations, remote sensing, process models, and top-down constraints, such as atmospheric CO_2 fields derived from the OCO-2 sensor, will provide an increasing clear picture of how forests are contributing to biosphere metabolism (Running et al., 1999; Schimel et al., 2015). The capacity to monitor global forest carbon flux will thus be an important component in understanding the degree to which forests act as a positive or negative feedback to the rising CO_2 concentration (Pan et al., 2011).

Evapotranspiration (ET) is the combination of evaporation of liquid water from land surfaces, transpiration of water through plants, and the sublimation of ice or snow. The energy required to evaporate water is the largest single heat source for the atmosphere, and ET is therefore a critical link between the planet's energy and water cycles (Vinukollu et al., 2011), and an important component of global hydrologic models. Significantly for monitoring of forests (and vegetated systems in general), ET is central to several drought stress indices (Anderson et al., 2010; Palmer, 1965). Resulting drought monitoring is useful in highlighting risk of fire and other forest health problems (X?).

Process-based Land Surface Models (LSMs) can be used to solve for ET (Chen et al., 1996), and remote sensing can provide important inputs to these models (Mu et al., 2011; Vinukollu et al., 2011). For example, Marshall et al. (2013) estimated ET from a time series of vegetation indices. Alternatively, an energy balance approach can be used with thermal imagery to infer ET. The Landsat thermal band, present since the launch of Landsat, has been used to estimate ET as a function of the difference between the observed surface temperature and the heat energy in the atmosphere (Allen et al., 2007; Su, 2002). This band, present since Landsat 3 in the late 1970s, has a ground resolution of approximately 100 m (varying to some degree across individual sensors). This spatial resolution is useful for resolving ET trends at scales that are relevant for management (Anderson et al., 2012), but Landsat's infrequent return interval, coupled with the fact that clear-sky observations are required, places limits the applications for which Landsat is appropriate. Thermal data from the Geostationary Operational Environmental Satellites (GOES), also available since the 1970s, provides a lower-resolution alternative that is available much more continuously (Anderson et al., 2010).

7. Future directions

Given the progress over the first four decades of remote sensing applications, it is of interest to consider current developments that will lead to enhanced capabilities in the future. The multispectral data sets at moderate (e.g. Landsat) and coarse (e.g. MODIS) resolution represent the backbone for assessing the dynamics and composition of managed forests. One emerging trend is the "MODIS-izing" of moderate resolution observations, that is, the ability to construct near-daily time series observations at <50 m resolution using multiple Landsat-type systems (e.g. Zhu et al., 2012). Data are now acquired by an international constellation of moderate-resolution systems including Resourcesat, CBERS, Sentinel-2, and Landsat. Harmonizing and merging just the Sentinel-2 and Landsat observations will provide $\sim$2–3 day coverage of the entire globe by mid-2016. While data availability remains a thorny issue, the technical means to provide daily, <50 m multispectral data exists today. A benefit of such a record would be the ability to derive biophysical variables (including vegetation phenology) at the scale of individual forest management units, as well as the ability to characterize short-term disturbances such as defoliation events or thinning.

New approaches for characterizing photosynthesis, productivity, and stress from remote sensing are gaining currency. As noted above, solar-induced fluorescence has been linked to photosynthetic uptake and light-use efficiency in laboratory measurements (Bilger et al., 1995; van der Tol et al., 2015), and more recently has been retrieved from satellite data (Joiner et al., 2011). The Photochemical Reflectance Index (PRI) has been shown to be indicative of vegetation stress (Drolet et al., 2005), and multi-angle approaches to retrieval appear promising (Hilker et al., 2011). Taken together, these findings suggest that we are on the cusp of being able to measure the canopy photosynthetic energy budget via remote sensing. While this capability would be useful for understanding primary productivity of forests, the real payoff might well be in understanding how climate variability *limits* productivity through stress. For example, tracking the response of SiF and PRI to evolving drought conditions may prove informative as we consider the vulnerability of managed forests to future climate conditions.

Structural measures from space are likely to evolve over the next decades as well. The trio of upcoming lidar and radar missions (NASA GEDI, NASA/ISRO NISAR, and ESA BIOMASS) should dramatically improve our knowledge of global biomass and forest structure during the $\sim$2020 era. A key opportunity, however, will be the extension of this one-time coverage to periodic inventories, at a resolution sufficient to derive stand-scale changes. Such a program would allow direct estimates of forest growth and losses for individual parcels globally. To date, however, no country has an operational program to conduct repeated surveys of forest structure from space.

More broadly, advances in information technology and miniturization of detector hardware are leading to connected "sensor webs" that span in-situ, airborne, and satellite platforms.

Networked phenocams (Richardson et al., 2007; Sonnentag et al., 2012), low-cost terrestrial lidar, and UAV-based hyper spectral and lidar systems (Watts et al., 2012) are starting to blur the lines between "field observation" and "remote sensing". As small, inexpensive UAV and autonomous in-situ sensors become ubiquitous, forest remote sensing will encompass continuous observations throughout the canopy.

8. Conclusion

In this paper we have reviewed some of the many opportunities provided by remote sensing to scale key forest ecosystem parameters over time and space, specifically those related to composition, structure, productivity, and disturbance. Forest management alters all of these parameters individually or (more commonly) in concert. The availability of diverse remote sensing modalities including multispectral, hyperspectral, radar, and lidar has steadily increased, and has led to improved ability to quantify multiple forest attributes, and understand how they are affected by management regimes. Some technologies (e.g. photosynthetic productivity estimated via solar-induced fluorescence) are only now emerging and may prove to be powerful tools in coming years.

As described in Section 2, the scaling of forest attributes may rely on interpolating inventory or plot data, process-based modeling, or novel combinations of each approach. Remote sensing has relevance to each approach and is often relied upon to produce landscape-to-global estimates of key forest ecosystem parameters. Plot measurements remain the "gold standard" for measurement accuracy, and when deployed as a systematic sample (e.g. in a well-designed forest inventory) such data provide unbiased area estimates with known sampling uncertainties. They do not, however, provide geospatial representation at the scale of forest management (i.e. the scale of individual stands). A challenge is to combine the measurement accuracy of plot and inventory data with the spatial breadth of remote sensing. A variety of approaches have been proposed to harmonize inventory and image-based attribute data, including the widespread k-Nearest Neighbor (k-NN) imputation approach, which preserves the statistical properties among sets of inventory-derived forest attributes (Tomppo, 1991; McRoberts and Tomppo, 2007). Additional complexity is introduced when the remote sensing measure itself is a geographic sample, as is the case for current global lidar datasets. In such cases, care must be taken to account for the sampling uncertainty of both the lidar dataset and the forest inventory, as well as the measurement error of lidar-derived structural variables (Healey et al., 2012; Wulder et al., 2012; Nelson et al., 2012).

Ecosystem models have leveraged a diverse range of remote sensing datasets in order to initialize parameters and provide validation of retrospective simulations. As discussed above, satellite-derived land cover and fPAR or NDVI are commonly used to parameterize vegetation composition and productivity, respectively, in biogeochemical models (Potter et al., 1993; Running et al., 2004; Zhao and Running, 2010). The Ecosystem Demography (ED) model is height structured, and can be initialized using lidar-derived forest heights to constrain carbon uptake (Hurtt et al., 2004). Disturbance information has been incorporated into some ecosystem models. Global fire datasets derived from AVHRR and MODIS have been used to provide CO and CO_2 fluxes for carbon balance studies (van der Werf et al., 2009). Finer-scale disturbance associated with forest management has been used in regional-scale modeling studies (Cohen et al., 1996; Masek and Collatz, 2006) or on a sampling basis for the United States (Williams et al., 2012). The recent publication of global maps of forest change at 30 m resolution (Hansen et al., 2013) allows for global-scale ecosystem models that include actual management dynamics. These observational data sets could be combined with moderate resolution, remotely-sensed vegetation and functional type maps to model ecosystem process dynamics at the level of individual, sub-grid cohorts of unique vegetation type and disturbance history.

One example of a model which explicitly combines maps of disturbance history with mapped forest structure and composition is the Forest Carbon Management Framework (ForCaMF), employed by the National Forest System to assess the carbon storage impact of management and different types of natural disturbance. The stand dynamics implied by these layers are linked to empirically calibrated carbon storage functions (Raymond et al., 2015) to enable modeling of storage under historical and hypothetical disturbance regimes. Monte Carlo simulation of error in each of the remote sensing products driving ForCaMF is calibrated directly from inventory data, providing integrated uncertainty estimates (Healey et al., 2014).

In principle, a new generation of diagnostic and prognostic models could be envisioned that would fully leverage the geospatial data available from contemporary remote sensing. Such models operating in a diagnostic mode might operate at the stand, or even the individual scale, and parameterize physiology based on species type and observable functional traits. Photosynthesis could be calculated directly from energy budget approaches via radiative transfer through the canopy, informed by information on canopy structure, canopy chlorophyll concentration, vegetation fluorescence, and stress indices (including thermal state, activation of the xanthophyll cycle, and pigments indicative of nutrient state). Long-term disturbance dynamics, including attribution of disturbance type and severity, could be parameterized from multispectral time-series combined with three-dimensional structure. Prognostic models of forest response to future climate or management scenarios could also harness remote sensing by confronting model hindcasts with observed, recent changes in vegetation attributes. When combined with in-situ inventory and plot data, such modeling approaches could provide rigorous, physically-based methodologies for scaling forest processes.

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