Chapter 26
Remote Sensing Tools for Monitoring Forests and Tracking Their Dynamics

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Abstract Remote sensing augments field data and facilitates foresight required for forest management by providing spatial and temporal observations of forest characteristics at landscape and regional scales. Statistical and machine-learning models derived from plot-level field observations can be extrapolated to larger areas using remote sensing data. For example, instruments such as light detection and ranging (LiDAR) and hyperspectral sensors are frequently used to quantify forest characteristics at the stand to landscape level. Moreover, multispectral imagery and synthetic aperture radar (SAR) data sets derived from satellite platforms can be used to extrapolate forest resource models to large regions. The combination of novel remote sensing technologies, expanding computing capabilities, and emerging geospatial methods ensures a data-rich environment for effective strategic, tactical, and operational planning and monitoring in forest resource management.

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26.1 Introduction

Forests play a primary role for life on Earth. Measuring and quantifying the state of forests at the landscape scale is critical from both a strategic and tactical perspective. Management-oriented forest monitoring efforts include complex and evolving objectives, such as timber production, environmental protection, biodiversity preservation, forest fire prevention, wilderness and open spaces, and adaptation to a changing climate. Forest monitoring approaches have continuously improved over the last few decades with innovations in remote sensing and computing methods. Although field surveys and inventories remain invaluable sources of information, the use of in situ methods to monitor critical forest metrics is limited at larger scales. However, with spaceborne and airborne remote sensing technology, forest monitoring efforts have advanced rapidly in terms of capacity, scale, and detail. For example, large swaths of land are imaged every day by Earth observation (EO) satellites, enabling the constant monitoring of global forest conditions (Mitchell et al., 2017). Such sizable remote sensing data sets provide opportunities to extrapolate the results of models derived from spatially limited field data to the landscape level and permit the observation of large-scale changes.

26.2 Remote Sensing of Forests

Earth observation satellites offer great opportunities to quantify landscape and regional land cover, composition, and change. Some of the commonly used satellite imagery include that from the National Aeronautics and Space Administration (NASA), National Oceanic and Atmospheric Administration (NOAA), European Space Agency (ESA), Indian Space Research Organization (ISRO), Canadian Space Agency (CSA), China National Space Administration (CNSA), and Japan Aerospace Exploration Agency (JAXA) (Table 26.1). Additionally, several commercial satellite imagery providers offer cutting-edge satellite data with higher spatial and temporal resolution and, in many cases, customized monitoring solutions. Some prominent commercial satellite imagery providers include DigitalGlobe from Maxar, Planet Labs, and Airbus. Commercial and openly available EO data are used in a wide variety of Earth science, forestry, agriculture, and geological applications by research, government, and commercial entities.

Some of the most common types of EO data include multispectral and synthetic aperture radar (SAR) systems. Examples of multispectral satellites include Sentinel-1 and 2, Landsat, the Moderate Resolution Imaging Spectroradiometer (MODIS), and the Advanced Very High-Resolution Radiometer (AVHRR). Of these, the higher spatial resolution satellites (e.g., Landsat and Sentinel) are generally more useful from a forest management perspective.

Table 26.1 List of satellite and airborne remote sensing instruments frequently used for forestry and land-cover applications; *RGB*, red, green, blue; *NIR*, near infrared; *SWIR*, shortwave infrared; *TIR*, thermal infrared, *MIR*, middle infrared; *Pan*, panchromatic; *SAR*, synthetic aperture radar; *LiDAR*, light detection and ranging; *NASA*, National Aeronautics and Space Administration; *NOAA*, National Oceanic and Atmospheric Administration; *ESA*, European Space Agency; *JAXA*, Japan Aerospace Exploration Agency; *USGS*, United States Geological Survey; *ISRO*, Indian Space Research Organization; *CSA*, Canadian Space Agency

Platform	Sensor	Agency	Imaging modes	Bands	Revisit time (days)	Spatial resolution (m)	Further information
Landsat-5	Thematic mapper (TM)	NASA/USGS	Multispectral	RGB, NIR, SWIR, TIR	16	30	https://www.usgs.gov/land-resources/nli/landsat/landsat-5
Landsat-7	Enhanced thematic mapper Plus (ETM+)	NASA/USGS	Multispectral	RGB, NIR, SWIR, TIR	16	30	https://www.usgs.gov/land-resources/nli/landsat/landsat-7
Landsat-8	Operational land imager (OLI)	NASA/USGS	Multispectral	RGB, NIR, SWIR, TIR, Pan, Aerosol	16	30	https://www.usgs.gov/land-resources/nli/landsat/landsat-8
Terra, Aqua	Moderate resolution spectroradiometer (MODIS)	NASA	Multispectral	RGB, NIR, SWIR, TIR, Vapor, Clouds, Aerosol, Snow, Ice, Ozone	1–2	250, 500, 1000	https://modis.gsfc.nasa.gov

(continued)

Table 26.1 (continued)

Platform	Sensor	Agency	Imaging modes	Bands	Revisit time (days)	Spatial resolution (m)	Further information
NOAA-satellites 6–19	Advanced very high-resolution radiometer (AVHRR)	NOAA	Multispectral	R, NIR, MIR, TIR	<1	1,000	https://www.avl.class.noaa.gov/release/data_available/avhrr/index.htm
ALOS-2	Phased array type L-band synthetic aperture radar (PALSAR)	JAXA	SAR	L-band	14	>7	https://www.eorc.jaxa.jp/ALOS/en/about/palsar.htm
Sentinel-1a and 1b	C-band synthetic aperture radar (C-SAR)	ESA	SAR	C-band	6	>5	https://sentinel.esa.int/web/sentinel/missions/sentinel-1
Sentinel-2a and 2b	Multispectral instrument (MSI)	ESA	Multispectral	RGB, NIR, Red-edge, Aerosol, SWIR	5	10, 20, 60	https://sentinel.esa.int/web/sentinel/missions/sentinel-2
Airborne	Airborne visible/infrared imaging spectrometer (AVIRIS)	NASA	Hyperspectral	224 bands	–	20	https://aviris.jpl.nasa.gov
Airborne	Land, vegetation, and ice sensor (LVIS)	NASA	LiDAR altimeter	–	–	5	https://lvis.gsfc.nasa.gov

(continued)

Table 26.1 (continued)

Platform	Sensor	Agency	Imaging modes	Bands	Revisit time (days)	Spatial resolution (m)	Further information
International Space Station	Global ecosystem dynamics investigation (GEDI)	NASA	LiDAR	Full waveform	–	25	https://gedi.umd.edu
ICESat-2	Advanced topographic laser altimeter system (ATLAS)	NASA	LiDAR	–	–	13	https://icesat-2.gsfc.nasa.gov
Cartosat-3	Multispectral VNIR (MX), Panchromatic instrument (PAN)	ISRO	Multispectral, Panchromatic	Pan, RGB, NIR, MIR	4	0.25, 1.2, 6, 12	https://www.isro.gov.in/Spacecraft/cartosat-3
RADARSAT-2	C-band synthetic aperture radar	CSA	SAR	C-band	24	1–100	www.asc-csa.gc.ca/eng/satellites/radarsat2
Dove, SuperDove, CubeSats	Planetscope imagery product	Planet Labs Inc	Multispectral	RGB, NIR	<1	3	https://www.planet.com/products/planet-imagery/
SkySat	SkySat	Planet Labs Inc	Multispectral, Video	RGB, NIR, Pan	4–5	0.5	
RapidEye	RapidEye	Planet Labs Inc		RGB, NIR, Red-edge	5–6	5–6.5	
Worldview-2	Worldview-2	Maxar Technologies	Multispectral	Pan, RGB, Red-edge, Coastal, NIR		0.5, 2	https://www.digitalglobe.com/products/satellite-imagery

(continued)

Table 26.1 (continued)

Platform	Sensor	Agency	Imaging modes	Bands	Revisit time (days)	Spatial resolution (m)	Further information
Worldview-3	Worldview-3	Maxar Technologies	Multispectral	Pan, RGB, Red-edge, Coastal, NIR, SWIR, Cloud, Aerosol, Vapor, Ice, snow		0.5, 2	
Worldview-4	Worldview-4	Maxar Technologies	Multispectral	Pan, RGB, NIR		0.31, 1.24	

The Sentinel satellites are part of ESA's Copernicus Program, one of the most recent and ambitious EO programs. Currently, there are two series of Sentinel satellites that provide data to users around the globe: Sentinel-1 and Sentinel-2. The former consists of a constellation of two satellites, 1A and 1B, carrying C-band SAR with a lower spatial resolution limit at 5 m. Spaceborne SAR is an active radar system that can image the Earth's surface with or without cloud cover and through smoke and other aerosols. Depending on the wavelength, microwaves from a SAR system can even penetrate the top layers of soil and vegetation and provide useful information regarding the soil's physical properties, such as soil moisture. The Sentinel-1 constellation can revisit the same location about every six days. Sentinel-2 consists of two multispectral satellites, 2A and 2B, having a spatial resolution of 10 m and a revisit time of five days. Multispectral satellite sensors measure how sunlight is reflected by the Earth's surface across a range of wavelengths and are passive in nature, i.e., without an active source of electromagnetic radiation. Figure 26.1 shows an example of SAR and multispectral images showing variations in backscatter and reflectance, respectively.

The Landsat satellite program offers the richest and longest-running historical archive of satellite data with observations since the 1970s (Wulder et al., 2019). This archive provides unique opportunities to study the mechanisms and extent of past and present forest dynamics. The moderately fine (30 m) spatial resolution of the Landsat Thematic Mapper sensors and their revisit time of 16 days make them uniquely suited for longer-term forest monitoring and management applications from space (Hansen & Loveland, 2012). The Landsat data archive became publicly available in 2008, which, combined with ready access via Google's Earth Engine

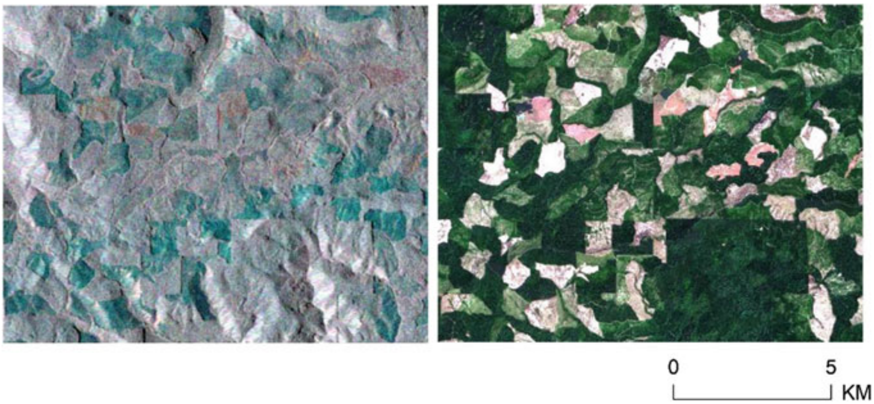

Fig. 26.1 Forest clear-cuts in western Oregon, United States, shown using (*left*) a Sentinel-1 SAR image composite with spring, late spring, and summer images as three bands in VV polarization and (*right*) a true-color image from a Sentinel-2 composite image using red, green, and blue bands from the summer 2018. SAR data are sensitive to topography, biomass, and water content. Recent timber harvest units have a higher color intensity in the SAR and lose seasonal variation as the forest regrows

platform (Gorelick et al., 2017), promoted the widespread use of these data for many research and commercial applications. Coarser spatial resolution satellites, such as MODIS and AVHRR, have historically been used to map and classify land cover at spatial resolution scales ranging between 250 m and 10 km. These coarse spatial resolution satellites have a high temporal resolution, with near-daily imagery, but their coarse resolution makes it challenging to derive reliable map-based estimates of forest characteristics and change (Chen et al., 2018). Although they have limited utility at local scales, MODIS and AVHRR satellites provide frequent remote sensing data that are useful for disaster monitoring systems and as inputs and validation for ecosystem models evaluating land-cover changes over large areas.

In addition to multispectral imagery, newer remote sensing technologies, such as light detection and ranging (LiDAR), provide emerging opportunities to assess boreal forest characteristics and can be used to quantify changes in forests over time (Dubayah & Drake, 2000). LiDAR can be used to estimate a variety of forest structural attributes across large areas, including canopy height, cover, volume, and biomass. Unlike multispectral sensors, LiDAR instruments actively emit photons via infrared lasers and then measure the amount of time required for the photons to strike a target and return to the sensor. Photon return time indicates the distance between the sensor and the target. LiDAR can be used to assess forest structure, including forest aboveground biomass (AGB), and reproduce subcanopy surface topography. LiDAR instruments can be airborne, spaceborne, or land-based (terrestrial) and can be used at different levels of detail to provide forestry-relevant management and inventory information (Magnussen et al., 2018; Shendryk et al., 2014; Zhao et al., 2018). Spaceborne LiDAR is increasingly being used to assess forest structure and biomass around the world. It has become progressively more feasible with photon-counting technology onboard ICESat-1/GLAS (2003–2009) and ICESat-2 (2017–present) (Popescu et al., 2018), and with the full waveform capability of the GEDI instrument (2019–present) (Dubayah et al., 2020). These new technologies are typically used to infer forest attributes at field sampling locations, which are further extended via remote sensing imagery across a larger area of interest on the basis of empirical relationships (Margolis et al., 2015; Neigh et al., 2013). Such methods can enable the rapid, robust, and cost-effective characterization of forest attributes across large areas.

In combination with the ever-increasing geospatial data being made available by multiple remote sensing and non–remote sensing sources, geographic information systems (GIS) are used as visualization, data manipulation, and processing tools for a wide range of data sets. The coevolution of GIS and remote sensing technologies has augmented field and inventory data with satellite imagery for map production, spatial visualization and query, and decision support (Sonti, 2015). Linking field inventory, aerial surveys, and remote sensing with GIS tools has helped foresters and ecologists develop more accurate records of forest cover, composition, and configuration for strategic (long-term) and tactical (short-term) planning.

26.3 Forest Biodiversity

Forest biodiversity is an essential consideration for sustainable forest management. Assessments of spatial heterogeneity in biodiversity commonly use satellite and aerial remote sensing data. In boreal environments, which have a moderate to low tree species diversity, such assessments may involve supervised and unsupervised classifications of high spatial resolution multispectral and hyperspectral data (Baldeck & Asner, 2013). Recent advances in data fusion techniques have enabled the use of high spatial and temporal resolution data combined with LiDAR (Fig. 26.2) from aerial platforms to measure and relate plot-level variations of species composition to environmental and physical factors (Powers et al., 2013; Rocchini et al., 2015). In addition to the analysis of tree species, remote sensing indicators have been used to model and map animal species diversity across large landscapes (Davies & Asner, 2014); for example, Coops et al. (2009) predicted bird species richness in Ontario, Canada, using productivity, topography, and land cover derived from remote sensing. Similarly, Kerr et al. (2001) modeled butterfly species richness on the basis of remote sensing–derived land cover and climate data. These studies also indicate that although biodiversity assessments can incorporate remote sensing approaches, it is seldom trivial to select remotely sensed indicators of biodiversity, and this approach requires a combination of traditional ecological knowledge and mathematical modeling.

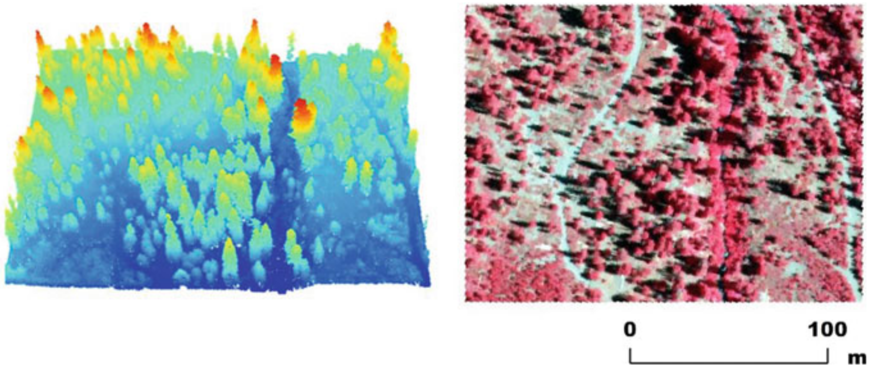

Fig. 26.2 (*left*) A LiDAR three-dimensional (3D) point cloud, color-coded by height from a baseline, of a small area in a Douglas fir–dominated forest. Data obtained from the United States Geological Survey's 3D elevation program (3DEP). (*right*) Airborne false-color imagery of the same area at a 1 m spatial resolution. Data from the United States Department of Agriculture's National Agricultural Imagery Program (NAIP) for 2018. In addition to the spatial location of individual trees, airborne LiDAR can capture the 3D structure of the forest

26.4 Forest Disturbances

Forest disturbances, such as wildfire, windthrow, and insect outbreaks, are integral and natural components of forest ecosystem dynamics. They impact forest species composition, structure, above- and belowground carbon storage (Alexander & Mack, 2016), forest regeneration and successional dynamics (Johnstone et al., 2010), as well as water and energy cycling (Goetz et al., 2012). Remote sensing methods can be used to detect and monitor forest disturbance across large areas and thus inform sustainable forest management policies and practices (Guindon et al., 2018; Hall et al., 2016). Ecosystem responses to disturbance events can be assessed using data from multiple satellite missions with field and airborne campaigns to monitor changes in connectivity, complexity, and heterogeneity across a region (Skidmore et al., 2015). The fusion of multilevel and multiresolution data can inform tactical and strategic management efforts. Such data collections can also be used to model ecosystem response to climate and help the strategic planning of resources in relation to future climate scenarios (Whitman et al., 2019).

26.4.1 Fire Detection and Risk

Fire occurrence and severity can be detected using multispectral satellite imagery by observing the difference in pre- and postfire indices, such as the normalized burn ratio (NBR) and infrared bands (Key & Benson, 2005). For fire management and detection, satellites such as MODIS. PlanetScope, and SkySat provide a daily updated stream of satellite images, which, when combined with aerial imagery, can be used to monitor fire progression (Giglio et al., 2016). During tactical planning stages, fire risk can be evaluated by assessing species composition, forest density, forest structure, and fuel conditions using a combination of airborne and spaceborne remote sensing data. The information storage and analysis capabilities of GIS tools are particularly useful for decision-making in tactical situations and emergencies where fire management and prevention, prescribed burning, and postfire recovery actions are planned by integrating GIS and remote sensing data to, for example, prepare maps of burn severity (Wulder & Franklin, 2006).

26.4.2 Monitoring Forest Health

Nonstand replacing disturbances, such as windthrow, insect outbreaks, and disease, often disproportionately impact certain tree species or sizes, leading to shifts in species composition, stand structure, and productivity (Goetz et al., 2012). Insect disturbances are usually observed indirectly in satellite imagery using specialized methods for each insect type (Senf et al., 2017; White et al., 2007). For example, once

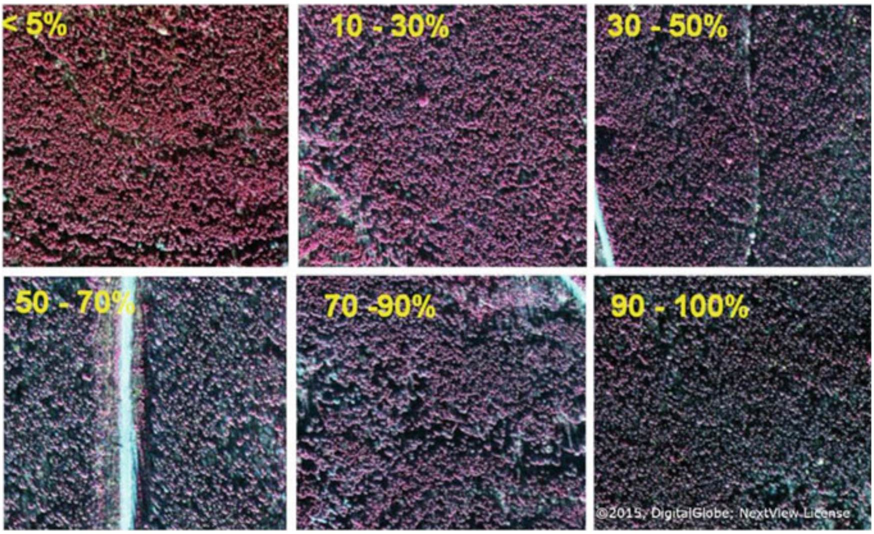

Fig. 26.3 Coniferous stands affected by the gradient of percent cumulative insect defoliation in a Canadian boreal forest as seen using 10 cm high spatial resolution false-color image and pan-sharpened shortwave infrared (SWIR) bands from the WorldView-3 satellite

infested by bark beetles, such as the mountain pine beetle (*Dendroctonus ponderosae*) or the spruce beetle (*Dendroctonus rufipennis*), the tree moisture status is often impacted through stomatal closure and secondary infection by fungal pathogens. Needle color changes from green to red (*red-attack* stage) or gray (*gray-attack* stage) depending on the tree species (Hall et al., 2016). The change in needle color, especially at the red-attack stage, is detectable in high-resolution multispectral imagery and can indicate insect infestation (Coops et al., 2006). The calibration and validation of insect disturbance mapping efforts are often achieved through comparisons with field data (Senf et al., 2017). For the long-term monitoring and detection of infestations, detection programs can employ annual aerial detection surveys as starting points to digitize validation polygons from the photointerpretation of high spatial resolution imagery (Meddens et al., 2012). Because of the inherent multi-scale nature of insect outbreaks, infestations occur at the individual tree scale but can quickly spread across landscapes (Raffa et al., 2008). Given that insect outbreaks often progress over several years, multidate time-series observations are usually required to detect and observe the complete response of a forest to an outbreak (Senf et al., 2017). Additionally, many infestation cases warrant the use of higher resolution remote sensing imagery (Fig. 26.3) from multispectral satellites, e.g., WorldView, hyperspectral imaging satellites, e.g., Hyperion, and aerial-based remote sensing instruments, e.g., airborne visible infrared imaging spectrometer, AVIRIS; Senf et al. (2017) and Makoto et al. (2013).

26.4.3 Invasive Species

The expansion of invasive species decreases the diversity of native plants and thus presents a threat to overall ecosystem resilience (Harrod & Reichard, 2001). Multi-date observations of changes in vegetation indices, such as the normalized difference vegetation index (NDVI) or enhanced vegetation index (EVI), can indicate an increased dominance of invasive species, especially where the invasive species are spectrally distinct from the native population. In cases where the invasive species are not spectrally distinct within multispectral imagery, hyperspectral imagery may be required to develop suitable models for detecting and mapping the encroachment of these invasive species (Huang & Asner, 2009). When there are structural or height differences between the native and invasive species, multispectral or hyperspectral data can be augmented using LiDAR or SAR data.

26.5 Forest Characteristics and Productivity

Forest management objectives are often achieved by monitoring and controlling forest characteristics in a stand to influence growth and yield. As large parts of the boreal forest are managed for wood production (Gauthier et al., 2015), remote sensing technologies provide effective tools to monitor stands, particularly when combined with field surveys and forest inventory data.

26.5.1 Assessing Forest Productivity with Remote Sensing

At landscape scales, remote sensing assessments of boreal forest productivity often rely on repeat measurements of coarse- or moderate-resolution multispectral data and vegetation indices (e.g., NDVI, EVI), SAR data, and airborne LiDAR. At the stand scale, however, tree species distributions derived from high-resolution multispectral data are often used to describe and project forest growth and yield (Modzelewska et al., 2020). Although field surveys traditionally determine species composition within stands, remote sensing tools can expand the field-derived models to larger scales. Such maps derived from remote sensing data also provide forest managers with the spatial distribution of products likely to be produced from the forest and also the vulnerability of stands to disturbance on the basis of tree species.

When it comes to measuring harvest potential and products that can be derived from forest stands, terrestrial and airborne LiDAR instruments are of primary importance. LiDAR data form an important part of growth and yield modeling simulations. Furthermore, tree-level data inform on both timber assortments and biodiversity. In addition to species distribution, stand density plays a major role in forest yield assessments and the monitoring of growth. In recent decades, airborne laser scanning (ALS) has emerged as a promising technology for estimating stand density within forested areas. ALS is a LiDAR approach that uses an airborne platform to transmit and measure returns from tree canopies in the near-infrared range. These returns can be used to accurately estimate the number of trees and stand density using spatial relationships between LiDAR points and "point clouds" (Næsset, 2004).

ALS-derived LiDAR point clouds can also be used to derive aboveground biomass and estimate stand age. As trees age, they typically grow in height up to a (usually species-specific) point, after which their vertical growth slows even as their carbon accumulation rate may continue to increase (Stephenson et al., 2014). Species distribution maps combined with stand-age data can be used to identify the site index, which is a measure of projected height at an index age (typically 25, 50, or 100 years). The site index is typically used as an indirect measure of site quality and its ability to produce specific wood products. Site quality is an essential parameter for forest managers as it can help determine the quantification of merchantable timber and is an essential input for the strategic planning of forest resources. Stand-age and site-index maps derived using remote sensing and GIS can also be used to identify harvest locations in the forest by identifying optimal mean annual increments (MAI) to maximize sustained volume productivity.

26.5.2 Mapping Forest Aboveground Biomass Using Remote Sensing

Forest aboveground biomass (AGB) describes the total dry weight of live trees per unit area and is related to structural metrics such as tree density, diameter, height, and composition. Forest AGB is useful for forest managers to consider because it provides additional information for volume estimates for timber production purposes, such as stand carbon sequestration and storage. Forest AGB maps may also serve as tools to identify areas of high conservation priority or with high intraspecific competition having a potential need of management treatments. Forest AGB can be mapped over an area of interest by linking plot-level forest inventories with remote sensing measurements related to forest canopy cover, structure, and composition (Berner et al., 2012; Puliti et al., 2020). Various remote sensing instruments are used to measure and map boreal forest AGB, including LiDAR, SAR, and multispectral sensors, often in combination with one another.

In addition to LiDAR, SAR data are used to map boreal forest AGB. Live-tree growing stock volume (GSV) is an important parameter for predicting forest AGB and can be mapped across large areas using SAR data (Santoro et al., 2015). Forest AGB can then be predicted by combining GSV with information related to land cover, land cover–specific wood density, and biomass allocation (Fig. 26.4; Thurner et al., 2014). Multispectral satellite imagery is an inexpensive means of extending AGB estimates from plot-level measurements through the use of airborne and terrestrial LiDAR,

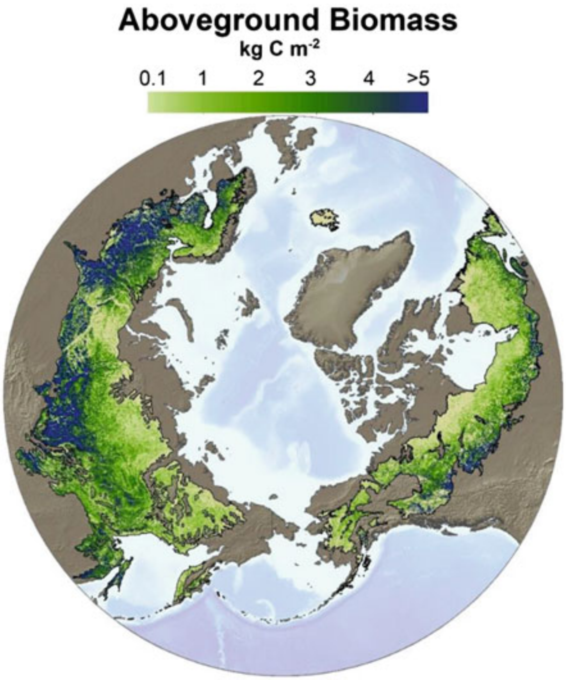

Fig. 26.4 Aboveground biomass mapped across the boreal forest biome using the synthetic aperture radar (SAR) and ancillary information (Santoro et al., 2015; Thurner et al., 2014). The boreal biome extent is based on the boreal ecoregions mapped by the World Wildlife Fund (Olson et al., 2001)

very high-resolution imagery, and field inventories. This multisource, multiscale approach can also be used to monitor changes in forest AGB over time. LiDAR data are particularly useful for augmenting multispectral imagery, as forest canopy closure obscures forest structure (Wulder et al., 2020). Ancillary geospatial information can also improve model predictions of boreal forest AGB (Puliti et al., 2020).

The integration of multispectral imagery with repeated LiDAR and SAR also provides emerging opportunities to assess boreal forest productivity by quantifying net changes in boreal forest AGB over time (ΔAGB), typically using either a *direct* or *indirect* approach (Karila et al., 2019; McRoberts et al., 2015). The direct approach involves predicting ΔAGB on the basis of differences in forest canopy structure between successive remote sensing measurements. The indirect approach involves predicting forest AGB at two points in time using remote sensing measurements and then computing ΔAGB by differencing the two predictions. The direct approach requires measurements from the same ground location during each survey, although prediction errors are easier to estimate. From an inventory standpoint, both methods can increase the precision of ΔAGB estimates relative to relying exclusively on field inventory measurements (McRoberts et al., 2015). Remote sensing efforts to quantify ΔAGB in the boreal forest have primarily relied on repeat airborne LiDAR surveys over small landscapes (Hopkinson et al., 2016; McRoberts et al., 2015). Recent efforts have also demonstrated the utility of spaceborne SAR to quantify ΔAGB, which allows for larger-scale mapping (Askne et al., 2018; Karila et al., 2019). Spaceborne LiDAR, e.g., ICESat-2, could also enable large-scale, sample-based estimates of ΔAGB in the boreal forest. The combination of satellite and airborne remote sensing provides a suite of tools for assessing boreal forest productivity at both the local and landscape scales.

26.6 Novel Technologies in Remote Sensing

Satellite programs such as Landsat, Copernicus, and MODIS provide a high degree of homogeneity of the data sets over time by ensuring fixed observation conditions, regular sensor and data calibration, and minimal geolocation errors. Such repeat observations are invaluable for evaluating and monitoring forest conditions at landscape scales over longer periods. Moreover, commercial petabyte-scale satellite archives of daily high-resolution images from providers such as Planetscope and SkySat from Planet Labs provide a constantly updated satellite data stream of the entire planet, ensuring global monitoring and data continuity for both tactical and strategic planning. These microsatellite constellations allow obtaining multiple measures of the same area of interest throughout a single season, which enables the study of phenological metrics in forest plots over several years.

However, large archives of satellite data present a major challenge in regard to processing and handling the collected imagery. Although large-capacity computing solutions can be built, such tools require significant time and resources and are only generally available within large institutions. Recent rapid advances in cloud-computing technology have increased the availability of on-demand computing capabilities for research and commercial users alike. Recently evolved cloud-computing technologies from Google Cloud Platform, Amazon Web Services, and DigitalOcean, to name a few commercially available platforms, are enabling researchers to push the boundaries of science by providing pay-per-use computing infrastructure. Cloud-computing services provide managed computational tools and platforms that can process large amounts of data without the need to install local computing infrastructure. Cloud-computing platforms, e.g., Google Earth Engine (GEE) (Gorelick et al., 2017), can help resolve challenges associated with the large amounts of computing required for working with and analyzing petabyte-scale satellite imagery data without interacting with it on a local computer. Many openly available satellite data collections, including Landsat, MODIS, Sentinel-1 and 2, and many derived regional and global products, are now available on GEE for user-defined processing and computation. Moreover, tools such as GEE are highly scalable and process satellite imagery in parallel, thereby markedly reducing time for many workflows. The scalable nature of GEE permits machine-learning workflows for classifying images.

The ability of forest managers to respond to the effects of changing climate on forests depends on effective data collection, processing, and derivation of actionable insights. Because it is not feasible to frequently or even infrequently census an entire forest using field surveys, it becomes necessary to monitor large tracts of forests for changes through remote sensing platforms and instruments. Models developed using a combination of field and remote sensing data can provide avenues for keeping forest managers informed of changes in biodiversity, biomass, vulnerability, stand density, and other forest characteristics. Future advances in remote sensing technologies, computing platforms, and geospatial software will further advance monitoring and mapping capabilities toward more sustainable planning and management of boreal forest resources and better equip forest managers for mitigating the consequences of ongoing climatic change.

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