Chapter 27
Remote Sensing at Local Scales for Operational Forestry

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Abstract The success of current and future forest management, particularly when dealing with triggered changes stemming from extreme climate change–induced events, will require prompt, timely, and reliable information obtained at local scales. Remote sensing platforms and sensors have been evolving, emerging, and converging with enabling technologies that can potentially have an enormous impact in providing reliable decision support and making forest operations more coherent with climate change mitigation and adaptation objectives.

27.1 Introduction

Forest operations are fundamental to the management needs specifically designed to respond to a trigger. These triggers are a planned sequence of events along the developmental stages of the stand that are set by the forest management plan during tactical or operational planning. Forest operations can also be a response

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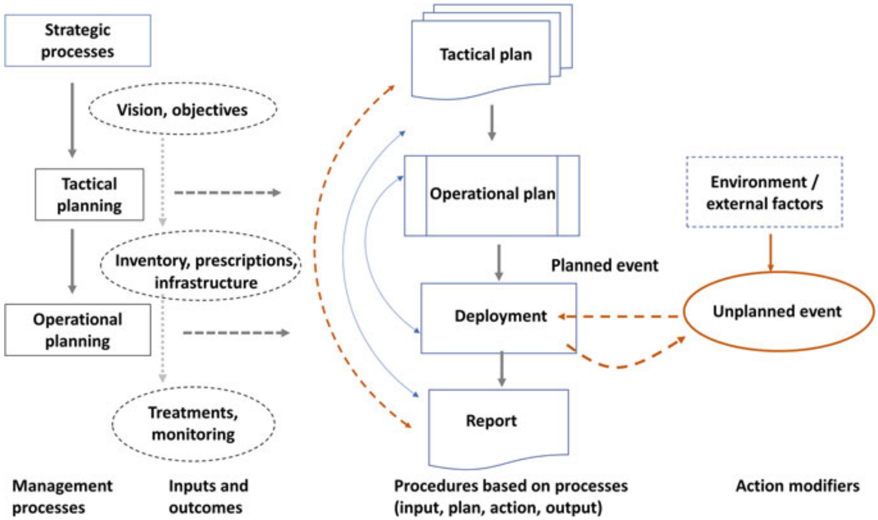


Fig. 27.1 Schematic of the general information flow (*gray arrows*), feedback loops (*blue arrows*), and feedback loops induced by a modifier (*dashed red arrows*)

to an unplanned change (unplanned trigger) that could alter the decision process and operation deployment, generating a feedback loop to the execution of the plan (Fig. 27.1).

Forest operations include timber harvests, fiber recovery, site preparation for suitable establishment (natural regeneration, seeding, or planting), thinning, pruning, timber stand improvement, competitive vegetation control, sanitization, and salvage (Fig. 27.2). They are designed to meet management needs (Fig. 27.1) on the basis of the targeted ecological response, technical applicability, and economic feasibility within compliance standards (Rummer, 2002). For example, harvesting within ecosystem-based management often prescribes the retention of legacy trees and the use of suitable techniques to avoid any damage to these trees. Whereas operations are a response to a planned trigger, they can also cause significant expected changes to the environment within a very short time; these changes also require tracking. For example, harvesting a matured stand will reset (change) the developmental process to its early-successional stages.

The effective implementation of sustainable forest management depends largely on carrying out sustainable forest operations (Marchi et al., 2018), which can prove to be more challenging in the context of climate change. The intensity and frequency of extreme climate events and severe insect outbreaks are predicted consequences of climate change and will alter the natural dynamics of the forests and drastically alter the local environment (Spittlehouse, 2005). For instance, operational deployment could be impeded by sudden flooding, early thawing, catastrophic tree damage, etc. The feedback loop to tactical planning in such situations happens rapidly and more frequently (Fig. 27.1).

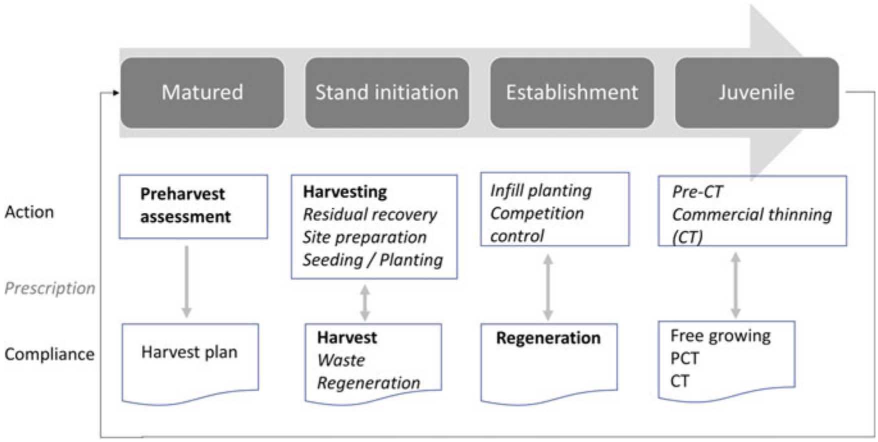


Fig. 27.2 Schematic showing various forest operations along the stand development stages *(dark gray boxes)*, including the critical operations (*bold*)

The success and efficient deployment and the completion of any response or action depend on a prompt, timely, and reliable information feed at the planning, deployment, and operational stages. The status of vegetation (e.g., tree species or stem quality) and terrain (e.g., slope or ground-bearing capacity) features are critical information needs (Table 27.1). Their level of detail, intensity, and periodicity is defined by the complexity of the type of operation or the environmental conditions in which the operation must be completed along the stand developmental stages (Table 27.1). For example, harvesting a sustainably managed mixedwood stand growing mainly on complex terrain conditions requires safe access to the site and detailed information on the targeted species, e.g., stem quality. It is critical to properly identify the seed trees and create microsites that favor natural regeneration during operations. Hence, information needs tend to relate to planning, i.e., a priori, and during the actual operation, i.e., real time. The recentness of the acquired data is also important. Moreover, detail intensity increases from a homogeneous plantation to a heterogeneous natural stand. The level of detail for planning a harvest operation may be at the tree to stand level for vegetation, whereas accessibility (surface, slope, skid trails, landings, and wood catchment zones) is generally required at the block level (Table 27.2). However, during the harvest operation itself, the required details are instantaneous, repetitive, and intense within the operator's line of sight.

Traditionally, data used for planning purposes has been based mainly on a priori ground surveys (e.g., walk-throughs, cruising—a method to determine value of a specific area—or inventory of plot installations) or coarse interpreted images. Treatment execution is completed using visual assessments and compliance reporting with independent surveys. Recent innovations in remote sensing technology for rapidly gathering, processing, and accessing information have significantly modernized how forest operations are planned and conducted. This chapter documents current remote

Table 27.1 Required information for vegetation and the post-harvest to complete a forest operation along stand development stages

	Matured	Stand initiation			Establishment		Juvenile	
Vegetation features	PHS	Harv	FibRec	SitePrep	Sd/Plnt	Compet	PCT	CT
Canopy								
Competing vegetation								
Crown balance								
Retention								
Species								
Stand structure								
Stem spacing/ occupancy/voids								
Stem location								
Tree height								
Vigor								
Stem								
Stem quality								
Tree damage								
Tree form								
Wood catchment/ volume								
Post-harvest								
Bucking/log sort								
Log scaling								
Residue distribution								
Residue geometry								
Stump								
Legend								
Action	Report	Both						
A priori	Real time	Both						

PHS, preharvest survey; *Harv*, harvesting; *FibRec*, fiber recovery, i.e., the process of calculating the recovery rate, removing residual fiber, secondary use of fiber, piling, burning; *SitePrep*, site preparation; *Sd/Plnt*, seeding/planting; *Compet*, competition, i.e., weed control; *PCT*, precommercial thinning; *CT*, commercial thinning

sensing technologies suitable for understanding, monitoring, and mapping forest conditions at local scales to plan, perform, and report forest operations successfully.

Table 27.2 Required information for the terrain and derived features to complete a forest operation along stand development stages

	Matured	Stand Init			Establishment		Juvenile	
Terrain features	PHS	Harv	FibRec	SitePrep	Sd/Plnt	Compet	PCT	CT
Roughness	Report	Action, Both						Action, Both
Ground bearing	Report	Action, Both						Action, Both
Obstacle	Report	Action, Both					Action, Both	Action, Both
Soil disturbance		Both, Both		Both, Both	Both, Both			
Slope	Report	Action, Both						Action, Both
Skid trails		Action, Both	Action, Both	Action, Both	Action, Both			
Drainage	Report	Action, Both				Action, Both		Action, Both
Derived features								
Accessibility		Action, Both	Action, Both	Action, Both	Action, Both	Action, Both	Action, Both	Action, Both
Safety		Action, Both	Action, Both	Action, Both	Action, Both	Action, Both	Action, Both	Action, Both
Cutblock boundary		Both, Both						
Hot spot			Both, Both					
Trafficability		Action, Both						Action, Both
Protected zones	Report	Both, Both				Action, Both		
Microsite availability				Both, Both	Both, Both			

Legend

Action | Report | Both

A priori | Real time | Both

PHS, preharvest survey; *Harv*, harvesting; *FibRec*, fiber recovery, i.e., the process of calculating the recovery rate, removing residual fiber, secondary use of fiber, piling, burning; *SitePrep*, site preparation; *Sd/Plnt*, seeding/planting; *Compet*, competition, i.e., weed control; *PCT*, precommercial thinning; *CT*, commercial thinning

27.2 Remote Sensing Platforms for Operational Forestry

Remote sensing is a platform-sensor combination (PSC) used to gather information about an object without being in physical contact with the object. PSC has the advantage of providing quick, synoptic, and repeated information over large and multiple spaces. The level of detail (coverage, resolution, timing, and frequency) varies with combinations of these various parameters (Table 26.2). Sensors are either passive (e.g., imaging/reflectance and thermal/radiation) or active (e.g., LiDAR or laser scanners and RaDAR or microwave scanners). The periodicity of the satellite data is fixed on the basis of constellations (daily to a few days; see Table 26.2), whereas all other acquisitions are programmed as per need (Tables 27.3 and 27.4).

Perception sensors help describe surface objects or perceive the environment. Positional or pose sensors (e.g., Global Navigation Satellite System–Global Positioning System, GNSS-GPS; Realtime Kinematics, RTK; Inertial Navigation System, INS; Inertial Measurement Unit, IMU; gyros and wheel encoders) determine the location and pose of the platform. A sensor platform refers to its carrier; these include

Table 27.3 Remote sensing platforms, their properties, and best uses for forestry applications

		Platform	Distance to object	Spatial resolution	Optimal temporal scale	Forest spatial scale under management	Sample applications
Mobile	Vertical range	Satellite (S)	700–35,000 km	Low to medium	15 days–twice daily	Landscape	Forest extent, biodiversity, drought, fragmentation, ecoclimatic zones, land-use class, disturbance regimes
		Aircraft/helicopter (A)	250 m to 12 km	Medium to high	>Daily	Stand–landscape	Species groups, roads/trails, drainage, terrain: elevation, slope, reconnaissance, disease, fire
		Drone (D)	<150 m	High to ultra-high	Near–real time	Tree–stand	Individual trees, tree species, biophysical estimates, hot spots, tree damage, subcanopy

(continued)

Table 27.3 (continued)

		Platform	Distance to object	Spatial resolution	Optimal temporal scale	Forest spatial scale under management	Sample applications
	Horizontal range	Machine (M)	<30 m	Ultra-high	Real time	Tree–subtree	Branching, tree form, occlusions, obstacles, regeneration, soil bearing capacity, soil disturbance, machine pose
		Human (H)	<30 m	Ultra-high	Real time	Tree–subtree	Branching, tree form, occlusions, obstacles, regeneration, soil bearing capacity, soil disturbance, bi-pied pose
		Stationary (T)	<30 m	Ultra-high	Real time	Tree–subtree	Branching, tree form, occlusions, obstacles, regeneration, soil bearing capacity

Table 27.4 Sensors and their platforms, vegetation analyzed with the sensors, and examples of use for vegetation and terrain analyses. Abbreviations for available platforms are given in Table 27.3

Suitable for forest operations–feature extraction

	Sensors		Available platform	Vegetation	Examples	Terrain	Examples
Perception	Imaging	RGB	All	Species/species groups, individual stem and location, stem spacing, occupancy, voids, tree height, vigor, retention, competing vegetation, residues: location, geometry, stump	Puliti et al. (2015), Natesan et al. (2020)	Slope, drainage, skid trails	
		MSS	All		Coops et al. (2007), Pouliot et al. (2019), Vepakomma et al. (2021)		
		Hyper	S, A, D, T		Modzelewska et al. (2020), Fassnacht et al. (2014)		
		RGB-D	D, M, H, T		Chandail and Vepakomma (2020), Li and Vepakomma (2020)		Murphy et al. (2008), Ågren et al. (2014)
	Radiation	Thermal Infrared	All	Hot spot: pile burn, disease, stem deterioration	Lagouarde et al. (2000)		
	Ranging	LiDAR	All	Stem quality, tree damage, tree form, volume, stand structure, stem and location, species, log scaling	Næsset (2007), White et al. (2013), Sibona et al. (2017), Holmgren et al. (2019), Vepakomma and Cormier (2017)	Roughness, obstacle, ground bearing, soil disturbance,	Ring et al. (2020), Rönnqvist et al. (2020), Talbot & Rahif, (2017), Chhatkuli et al. (2012)
		RaDAR	S, A	Species group, stand structure	Andersen et al. (2008), Tighe et al. (2009)	Trafficability, bearing capacity, water depth	

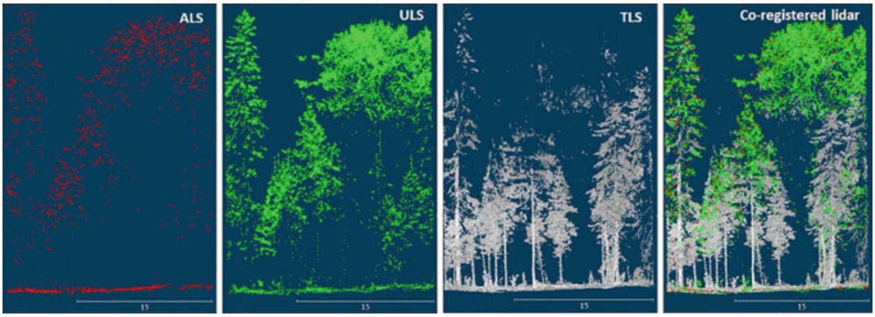


Fig. 27.3 Comparison and coregistration of LiDAR point clouds of a coniferous stand as captured from various platforms. *ALS*, aerial LiDAR; *ULS*, UAV-based LiDAR; *TLS*, terrestrial LiDAR)

mobile platforms, such as satellites, airborne platforms (aircraft and drones, also known as *unmanned aerial vehicles* or UAV), manned or unmanned ground vehicles, and human or stationary platforms, such as towers and tripods. Sensors are also sometimes distinguished by the platform they carry; for example, Liang et al. (2015) classified laser scanners as being either airborne (ALS), terrestrial (TLS), mobile (MLS), or personal (PLS). Platforms above the forest canopy can provide a synoptic view over large contiguous areas to provide a top-to-bottom description. In contrast, platforms in proximity, below the canopy, or closer to the ground provide vertical stem information and a detailed terrain description that is not feasible or possible from above-canopy platform systems (Fig. 27.3). For example, Kankare et al. (2014) demonstrated that TLS produces preharvest tree- and stand-level bucking details at a greater degree of accuracy than conventional means. Such data can help estimate the stumpage value of a stand or more suitable wood assortments.

Optical sensors capture the reflectance from materials within, e.g., standard digital RGB camera, and beyond the visible spectrum, e.g., infrared, whereas thermal sensors capture radiation from materials. Multispectral sensors (MSS) capture reflectance in limited or broad spectral regions (bands), and hyperspectral sensors have narrower but multiple bands. The spatial resolution of the image represents the ground sampling distance (GSD), which varies on the basis of the focal length of the sensor, the altitude at which the sensor is placed, and the speed with which the platform moves (Table 26.2). For instance, depending on the sensor platform, GSD may vary from a subcentimeter (e.g., drone), to submeter (e.g., WorldView series) to kilometer (e.g., AVHRR) scale. GSD is important in determining the spatial resolvability (*mappability*) of the feature on the image. Typically, assuming a reasonable contrast of the target feature from its background, more than 3 cm GSD is recommended for manually discerning trees as small as 0.4 m in height with a 35 cm crown diameter or form on an image (Pitt et al., 1997).

LiDAR (light detection and ranging) and RaDAR (radio detection and ranging) are active ranging sensors. RaDAR transmits microwave radio signals, whereas LiDAR transmits infrared energy. Both emit pulses that can penetrate through smoke, cloud, and small openings in tree canopies to reach the forest floor as well as measure the reflected backscatter. The range is converted to distance to provide precise locations (*x, y, z*) of the point of interaction with an object in space, and these sensors are best suited to describing the structure of an object, e.g., crown shape or tree height. Available radar systems provide a spatial resolution larger than 1 m and are better suited for large-scale mapping relevant to strategic or tactical forest management.

In terms of the capabilities of data recording, LiDAR systems can be fullwave (complete distribution of intercepted and returned laser pulse along the pathway) or discrete return (few observations are recorded from a laser pulse that is intercepted and reflected from targets). As they record the entire pathway along with the additional attributes of amplitude and intensity, fullwave systems are better suited for detailed above- and below-canopy characterization. Fullwave recording requires large-scale data management and algorithms, and this approach still remains at the experimental stage; however, discrete LiDAR is currently in operational use (Crespo-Peremarch et al., 2020). LiDAR systems are also differentiated by laser footprint size. A small footprint (less than one meter) on the ground provides a good link between the LiDAR beam and the structural vegetation attributes that are subtle among or within individual trees. By segregating the returns, e.g., vegetation versus ground, the points can be interpolated to describe continuous object (*digital surface model, DSM*) and terrain (*digital terrain model, DTM*) surfaces. Their arithmetic differences represent the aboveground surfaces, e.g., *canopy height model* (*CHM*). Point clouds, as well as surface models, are used to extract features. Point density and the power of the laser signal to penetrate through the canopy define feature resolvability and the estimated dimensions. Because imaging sensors receive the resulting light reaction from a particular surface, they tend to be best suited for understanding floristic compositional/structural characteristics related to the object, e.g., species, vigor, canopy cover, and density. Imagery is a 2D raster, and LiDAR is 3D point data or vertical profile; however, when images are gathered either as a stereo or overlapping sequence, they can provide photogrammetric 3D data useful for describing the structure of objects, such as canopy structure. Table 26.2 highlights the estimable direct/indirect features relevant to forestry on commonly available platforms.

The selection of PSC for a forest operation depends on the spatial extent and patterns of the area of interest, the timing, the recentness of the acquired information, and the repetitiveness between triggers for the required monitoring/reporting, specifically for vegetation status. Preharvest surveys should be within a year of the operation, whereas site preparation for competition control is conducted within a month, and regeneration surveys are two to five years after stand initiation (Table 26.1). The availability of certain RS platforms, such as satellite or aerial platforms, may be limited. Similarly, the phenology of target vegetation is an important consideration, as coniferous crops remain distinctly visible during the early spring or late fall, whereas deciduous vegetation is transparent during these periods.

Measurements with static terrestrial platforms provide a single or a small number of viewpoints and hence are limited to the validation or calibration of models built on higher platforms (Liang et al., 2018). On the other hand, mobile systems have the potential to provide near-real-time data and detailed below-canopy data relevant for operational decisions (Holmgren et al., 2019).

27.2.1 Positioning and Tracking Systems

Precise positioning in space and navigation is essential for safe and effective target action through localization (e.g., fire, salvage, or herbicide sprays) or tracking activity data (e.g., machine movements or harvest operations) for assessing efficiency, quality, and productivity (Keefe et al., 2019). The most commonly used positioning tools are *global positioning systems* (GPS) operating via a constellation of satellites, 24 as in GNSS. A GPS receiver can provide latitude, longitude, elevation, and the vector heading to monitor one's location on topographic/thematic maps or imagery (Picchio et al., 2019). This information is generally integrated with a geographic information system (GIS) and can be visualized by the operator. Differential GPS or RTK systems can improve locational accuracy. Given the poor precision in forested environments because of canopies blocking satellite signals, additional sensors like INS can be used to estimate relative position and orientation of a mobile vehicle, e.g., an operating forestry machine. The heart of INS is the IMU—a combination of gyroscopes, accelerometers, and magnetic sensors used for determining translational and rotational velocity to provide a navigational solution. More recently, simultaneous localization and mapping (SLAM), a technique popular with autonomous systems, has also been tested for use in forestry (Chandail & Vepakomma, 2020; Tang et al., 2015). SLAM involves creating a map for an unknown environment while simultaneously determining the agent's location using a laser or RGB-D camera to estimate depth in combination with other location sensors, such as GPS and IMU.

27.3 Remote Sensing–Based Feature Extraction for Forest Operations

In the context of a forest operation deployment sequence, we can essentially discuss remote sensing technologies as those (1) providing information on the forest environment for operational planning, monitoring, or assessing the effectiveness of an operation and/or reporting compliance; (2) gathering environmental information during the operations; and (3) relating to the operations themselves. Essentially, planning is a priori information that has a recentness from the day to a few months previous and helps determine the selection and use of machine systems. Information used for compliance or when monitoring effectiveness following a treatment must also be recent, whereas data needs are real time to near–real time for the deployment of actual operations. Above-canopy platforms are more suitable for planning and monitoring, especially in contiguous spaces, whereas close-range, terrestrial, and mobile platforms are most suitable for real-time operations. The following subsections are organized to understand how remote sensing, especially using platforms closer to the canopies, can be used for information feed, particularly in relation to vegetation and the underlying terrain, as highlighted in Table 27.1, along the sequence of a forest operation deployment. We provide, where possible, examples of different applications.

27.3.1 Vegetation Features

During the stand development stages, many prescriptions call for vegetation changes to the established stands, e.g., harvesting of crop trees, regeneration cuttings in shelterwood or group selection systems, thinning, sanitation removals of diseased or infested trees, or the spraying of herbicides on competing shrubs that affect crop tree growth. These prescriptions require accurate data at the subtree, tree, or, at the least, microstand level for efficient and effective management. This relevant data includes assessing tree height, form, quality, vigor, and species, as well as the tree's surrounding environment, e.g., stocking, growing space, species mix, and competition.

27.3.1.1 Pretreatment Assessment

Given its ability to reconstruct 3D forest structures and reliably estimate several biophysical parameters describing within- and below-canopy structure and function, LiDAR has become an essential component of operational forest inventories in numerous countries (Maltamo et al., 2021; Næsset, 2007; White et al., 2016). Two main approaches for LiDAR have been developed: an *area-based* and an *individual-tree* approach. The former is aimed at large-scale assessments that have a coarse point density effective for producing a stand portrait. As the name suggests, the individual-tree approach relies on identifying and delineating trees, including species identification, direct estimation of height and crown parameters, modeled diameter at breast height, basal area, and volume. The area-based approach (ABA) is a model-based estimate in which canopy descriptors or metrics are predicted on the basis of regression or discriminant analysis using accurate in situ plot data and height distribution (quantiles, percentiles, etc.) of LiDAR beam reflection (White et al., 2013). This method has demonstrated an accuracy of 4–8% for stem height, 6–12% for mean stem diameter, 9–12% for basal area, 17–22% for stem density, and 11–14% for volume estimates in boreal forest studies attempting to capture within-stand variability (Holmgren, 2004; Maltamo et al., 2010; Næsset, 2007; Sibona et al., 2017; White et al., 2013). In the absence of tree-level information, this stand or microstand level of characterization has been applied in eastern Canada to aid silvicultural prescriptions, such as commercial thinning or salvaging (Lussier & Meek, 2014; Meek & Lussier, 2008). Integrating vigor information with LiDAR canopy stratification helped machine operators improve productivity by 4% (Fig. 27.4; Gaudreau & Lirette, 2020). Area-based estimates using digital aerial photogrammetry collected across a range of boreal forest types is comparable with that obtained via aerial LiDAR (Goodbody et al., 2019). McRoberts et al. (2018) and Fekety et al. (2015) note, however, some challenges of using ABA models in relation to their shelf life and temporal transferability.

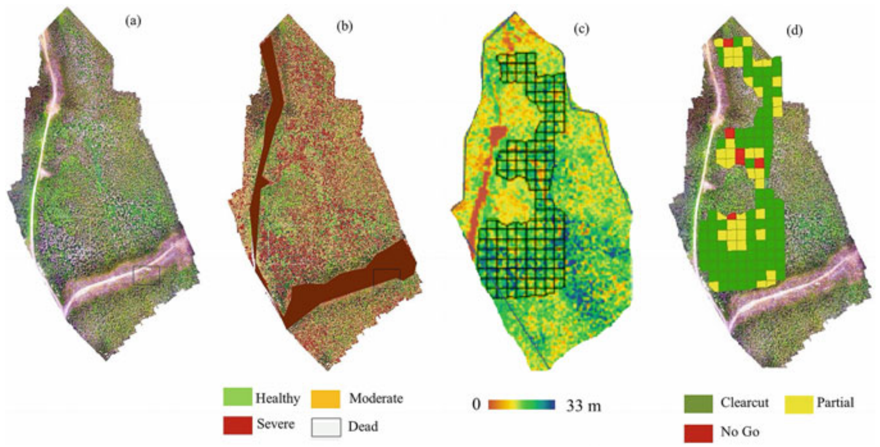


Fig. 27.4 LiDAR-based stratification combined with image-based vigor for silvicultural prescription and operator assistance **a** ortho image, **b** vigor class, **c** canopy height model, and **d** logging map

The extended history of aerial and satellite platforms carrying optical sensors, more recently combined with LiDAR, has produced a large body of work demonstrating the successful implementation of remote sensing to studies of canopy vegetation (Cerrejón et al., 2021). Multiple approaches exist for quantifying and estimating the structural and compositional parameters of interest and spatially mapping these parameters at various spatial scales. Generally, very-high-resolution imagery in 2D, stereoscopic, or overlapping imagery in 3D is visually interpreted based on the calibration of a series of field plots combined with guidelines related to the vegetation in terms of foliage color, texture, crown shape, and branching structure (Corbane et al., 2015). Semi- or fully automated workflows can be summarized as segmenting the image into homogeneous objects (a tree, a collection of trees, or a stand) and then (1) estimating directly the structural or compositional parameters of interest or (2) estimating these parameters indirectly through proxy variables. Segmentation, in particular individual tree crowns (ITC), is 2D raster-based (either multispectral images, grayscale images, or CHM) and 3D point clouds (photogrammetric or LiDAR).

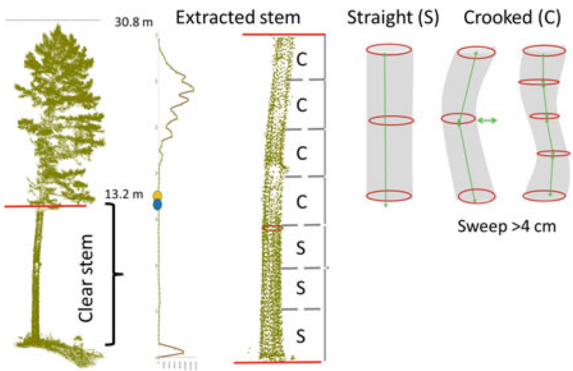
Separating vegetation from its background and assuming the brightest pixel to the highest point of the foliage on high-resolution 2D images (similar to raster-based CHM models), rule-based semi- or fully automated approaches can then extract tree crowns. Accuracy varies with GSD and by partitioning images into homogeneous forest stands; for instance, an accuracy of 60% (70 cm resolution) to 89% (31 cm) has been estimated for open coniferous to more complex mixedwood boreal forests, respectively (Katoh & Gougeon, 2012; Leckie et al., 2005). The number of trees per species depends on ITC accuracy, which improves when understory species are eliminated. Two-dimensional models may help with segmentation when estimating species density, although the structural assessment of canopies also requires determining canopy height.

Digital aerial photos (DAPs) combined with stereoscopic (visual) or digital photogrammetry can reconstruct a 3D forest canopy. Image matching and, more recently, computer-vision techniques such as SIFT (*scale-invariant feature transform*) combined with *structure from motion* (SfM) are very commonly used to estimate the 3D forest canopy from sequences of overlapping 2D images, e.g., images captured from a drone. If an accurate DTM is derivable, which can be difficult in complex, mature stands, DAPs can estimate the structural variables of the uppermost canopy, e.g., height, basal area, volume, quite accurately, comparable with the accuracy obtained using aerial LiDAR (Baltsavias, 1999; Goodbody et al., 2019). When DTM from an image is not derivable, a simple solution is to have a coregistered LiDAR or SRTM DTM for DAP point normalization or canopy surface generation (St-Onge et al., 2015). Three-dimensional forest canopy models can be useful for silvicultural prescriptions when data acquisition is optimally timed before an operation is planned. It is also possible that rapid and near-real-time inventory measurements, e.g., canopy cover, based on ocular estimates are made with an improved precision using nadir—the sensor looking vertically downward—images from a drone. UAV-SfM estimates of several inventory variables are comparable to those of LiDAR in terms of root mean square error for dominant height (3.5%), Lorey's height (13.3–14.4%), stem density (38.6%), basal area (15.4–23.9%), and timber volume (14.9–26.1%) (Puliti et al., 2015; Tuominen et al., 2015).

Although raster-based ITC approaches can segment most of the top canopy, potential segmentation within the multilayered vertical structure of the canopy to capture subcanopy elements—especially using LiDAR echoes from above-canopy platforms—is possible through point-based clustering. Hamraz et al. (2016) obtained >94% detection rate for dominant and codominant trees in complex stands. Because of the ultra-high-density data in current LiDAR systems, there is also a greater possibility of extending techniques to direct and nondestructive estimates of a suite of stem-quality determinants with a high level of accuracy, including estimates of crown base, clear stem, stem taper, stem straightness, and branchiness (Vepakomma & Cormier, 2017, 2019). This offers great potential in the more refined selection of trees on the basis of target mill product specifications and automated bucking, where each tree can be analyzed at the stump to optimize its market value (Fig. 27.5).

Distinct tree architecture and branching patterns can be observed from high density LiDAR (Fig. 27.5). A 77.8% accuracy has been achieved in distinguishing predominantly boreal tree species by correlating estimated LiDAR features to vertical and horizontal foliage patterns (Li & Hu, 2012). Use of the textural or spectral intensity of multiwavelength LiDAR improved the accuracy (Budei et al., 2018). However, given the easy availability of optical images, spectral-based species discrimination is the most suitable, rapid, and pragmatic means of mapping large forest spaces.

Accuracy in tree species classification has improved through a priori crown extraction (Dalponte et al., 2014), although Heinzel and Koch (2011) found pixel-based classification improved the undersegmentation of crowns. While very-high spatial and super-spectral-resolution images such as the Worldview series are promising, the automated discrimination of more than ten tree species has been achieved with 82% accuracy using high-spatial-resolution MSS data (Immitzer et al., 2019). Accuracy



	Along the clear stem	Along the crown		
	Consecutive 2 m straight Sections*	Number of 2.44 m logs		
TREEID	S, straight; C, crooked, N, no data available	HIGH	MED	LOW
1667	C,S,S,S,N,N,S,C,S	4	0	0
1958	S,C,C,C,C,C,C,C,C,S,C,C,S	2	0	0
297	S,C,N	3	1	0
906	C,C,S,S,N	4	2	0
2603	S,N,S,S,S,C,C,S,N	4	0	0
1804	C,S,S,N,S,S,S,S,C,C,S,C,N	1	0	0
1742	S,S,S,S,S,S,C,C,C,S	3	1	0
817	C,S,S,S,S,S,S,C,C,N	3	0	1
1162	S,C,S,C,S,C,S,N	2	0	0
1141	C,C,S,N	3	0	0
1598	C,C,C,C,S,N,N,N,S,C,C,N	1	0	0

***Example:** *In tree 1742, a consecutive S,S,S,S,S,S of 2 m logs results in a 12 m straight section of the stem*

Fig. 27.5 Estimating wood-quality determinants using ultra-high-density LiDAR. Modified from Vepakomma and Cormier (2019),

improved greatly when models were adapted to narrowband hyperspectral sensors (Fassnacht et al., 2014; Modzelewska et al., 2020). Hyperspectral data, nevertheless, is data- and process-intensive and is restricted to being the most successful when collected in bright light conditions. Some researchers have found that sensor-fusion approaches, such as MSS or hyperspectral data with LiDAR, have improved species discriminability in boreal regions (Dalponte et al., 2014; Trier et al., 2018). These models identified as many as 19 species at 87% accuracy. Because temporal variability is a critical factor for species discrimination and there is an existing insufficiency of training samples, drone-based solutions can serve to map at local scales and develop a reference database (Fassnacht et al., 2014; Natesan et al., 2020). After iteratively building tree libraries from drone-based simple RGB images acquired in variable light-season-year conditions, Natesan et al. (2020) discriminated five conifer species at 73–91% accuracy (Fig. 27.6) and adaptively improved this library to identify six more deciduous taxa at over 79% accuracy in boreal regions.

An indicator of forest health is a forest's resistance and resilience to disturbances and its ability to adapt to climate change over the long term. Altered structure, functioning, or taxonomy because of the physiological stress of resource limitation, disease, or disturbances occur at all spatial (vertical and horizontal) and temporal

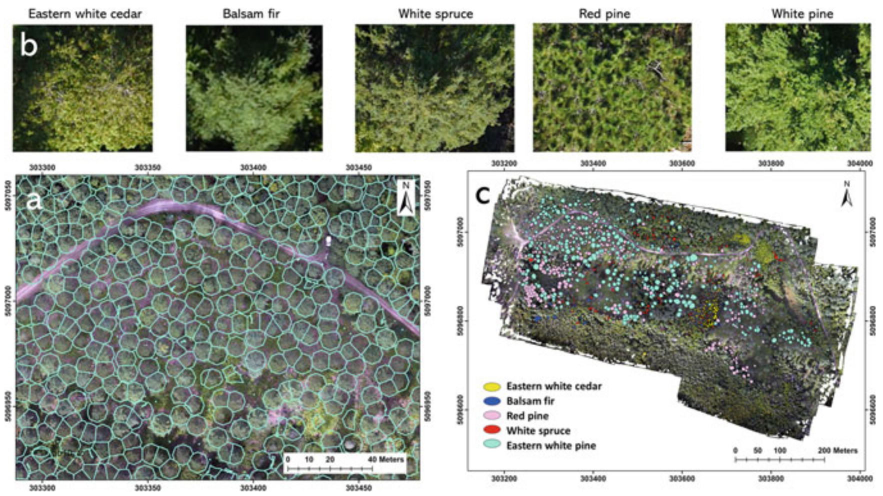


Fig. 27.6 Tree species recognition using an extensive image library from UAV-based RGB images; **a** automated crown delineation, **b** extracted crowns for training, **c** softwood species classification. Modified with permission from Canadian Science Publishing, permission conveyed through Copyright Clearance Center, Inc., from Natesan et al. (2020)

scales; nevertheless, capturing early signs can help minimize disturbance-related damage. Using the concepts of spectral traits and their variability (direct or proxy variables of forest health), Lausch et al. (2013) conducted an extensive review of the best PSC and available techniques for quantifying or qualifying short- to long-term monitoring of vigor. Close-range sensing improves precision or calibrates spectral responses of stress or disturbance in airborne remote sensing (Fassnacht et al., 2014). Slight declines in chlorophyll or moisture levels (identifiable through hyperspectral sensing) have helped provide early warnings of bark beetle (Fassnacht et al., 2014; Safonova et al., 2019) and herbivorous insect (Cardil et al., 2017; Meng et al., 2018; Vepakomma et al., 2021) infestations. There has been some success in identifying isolated impacted trees to group mortality (Fassnacht et al., 2014; Sylvain et al., 2019) and distinguishing the effects of multiple disturbances, e.g., pine blister rust and mountain pine beetle (Coops et al., 2003; Hatala et al., 2010).

27.3.1.2 During Treatment

Planning and executing forest operations is as much about following best practices as it is avoiding changing or damaging cultural remnants and special biotopes or transgressing property borders. LiDAR has been used to detect cultural heritage sites (Risbøl et al., 2014) and map habitat characteristics with the possibility of earmarking areas that must be avoided (Evju & Sverdrup-Thygeson, 2016). Proximal scanning also shows a strong potential in providing decision support during operations. For example, the rapid detection and estimates of stand density, tree position, and stem diameter (Holmgren et al., 2019) has helped with thinning tree selection and allowed data to be collected on individual tree selection by harvester operators through modeling of which tree the operator might select a priori (Brunner & Gizachew, 2014) or during operations (Gaudreau & Lirette, 2020).

27.3.1.3 Post-operation Monitoring

In most jurisdictions, standard practice involves compliance of contractual or regulatory frameworks and a post-operation follow-up; for example, these can entail assessment of post-harvest renewal or establishment monitoring to ensure sustainable production. The desired management objectives are typically to control stocking, species composition, survival, and growth. The distinct conical shape of conifer seedlings allows their easy detection for both planted trees and natural irregularly spaced stems. Vepakomma et al. (2015) distinguished conifer seedlings at least 0.3 m in height and estimated their size with a low average bias of 0.02 m through simple RGB images obtained from a drone. The data formed a basis for evaluating stocking, growing space, and regeneration gaps. By distinguishing competitive species, the models were further extended to qualify free-growing trees and assess regeneration compliance (Fig. 27.7). Pouliot et al. (2002) found that although the automated detection of six-year-old planted conifers was significantly high (at 91%), crown size extraction was sensitive to pixel resolution. In their case, they noted an 18% error compared with field assessments.

27.3.2 Terrain Features

The cost, efficiency, and potential environmental impact of forest operations all depend greatly on terrain features, e.g., surface roughness, slope, obstacles, and hydrographic data (flow channels, slope, drainage, and wet areas). These features can be described at macro-, meso-, and microlevels. DTM at corresponding resolutions are derivable using RaDAR interferometry, e.g., inSAR from satellite, available SRTM (Shuttle RaDAR Topographic Mission) data, LiDAR, or images using photogrammetric techniques where the ground is visible (Talbot & Rahif, 2017). Given the current technologies, LiDAR has proven to be the best available and most accurate tool for terrain assessments of mature stands. However, ALS with coarse data density can still provide a resolution greater than what planning methods can actually use (Talbot & Rahif, 2017).

Knowledge of terrain surface roughness and the number of potential hazards, especially under a dense canopy or on steep slopes, is critical for operational safety. Full-waveform LiDAR has a higher chance of returns from dense terrain and enables the successful detection of hazards, such as protruding rocks over 2 m wide (Chhatkuli

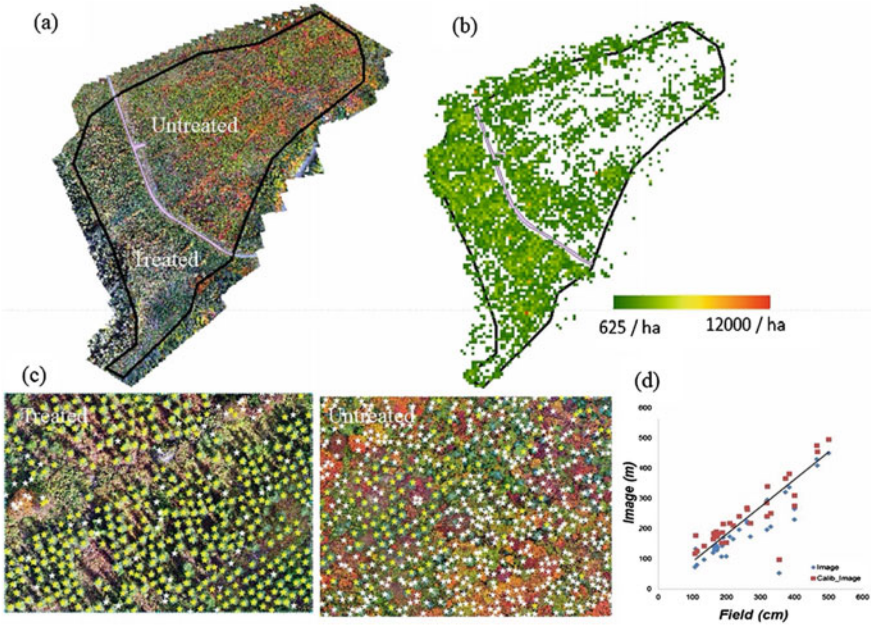


Fig. 27.7 Automated coniferous regeneration assessment for UAV-based RGB images for reporting compliance; **a** orthorectified image, **b** species group map, **c** species-wise detected individual stems, **d** stem height calibration model

et al., 2012). Slope and hydrographic features are directly derivable from a DTM, and model-based indices are used to identify wet areas and surface roughness (Ågren et al., 2014; Murphy et al., 2008). Identifying surface features that could be potential hazards helps ensure the safe driving of machinery at a harvest site (Fig. 27.8; Li and Vepakomma, 2020). Wet-area maps, which are characterized by indices such as cartographic depth-to-water (DTW) or the topographic wetness index (TWI) help to assess soil, vegetation, and drainage type and are used by the machine operators during forest operations to avoid or mitigate site damage (Ring et al., 2020). Such maps constitute a considerable improvement in recent forest management data and the planning of forest operations (Talbot & Astrup, 2021).

27.3.2.1 Pretreatment Assessment

Harvesting planning. Forest operations alter the environment, which, most often, is desired and intended. Undesirable impacts occur in particular when moving material or equipment into the forest (Rummer, 2002). In practice, machine operators in Europe and the Americas use tree cover and ground information as a canvas to plan harvesting or the moving of equipment. Providing an automated feature extraction

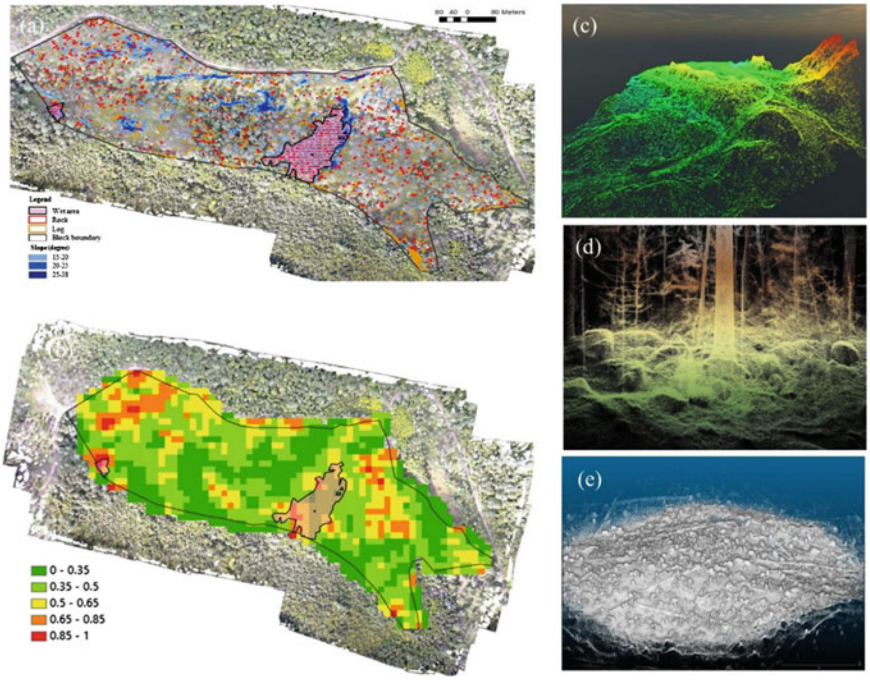


Fig. 27.8 Hazard detection and model-based drivability map using ultra-high-density LiDAR data from a UAV; **a** detected hazards overlying an orthorectified RGB image, **b** modeled drivability index showing a gradient of drivable (*green*) to no-go areas (*red*), **c** digital elevation model, **d** rock outcrops captured by mobile LiDAR, **e** extracted stumps. Modified with permission from Li and Vepakomma (2020)

from remote sensing as part of harvest planning can significantly minimize detrimental factors. These features can then be fed into algorithms to identify potential landings adjacent to roads or aid route optimization (Flisberg et al., 2021). In ground-based harvesting, the skid trail layout should be adapted to both the topography and the soil bearing capacity. Rönnqvist et al. (2020) combined digital elevation models, depth-to-water maps, and LiDAR-based tree volumes to spatially optimize extraction routes. In steep terrain, identifying suitable load paths for cable yarding and maximizing the use of each yarder setup is essential for optimizing economic performance. Detection of suitable end trees (tail spars) and intermediate support trees and discerning actual terrain form between contour lines—previously carried out by manual profile surveys—can now be easily replaced by LiDAR assessments (Dupire et al., 2015; Søvde, 2015).

Roads and transport. Monitoring forest road conditions includes gathering information on road geometries, surface conditions, condition of the drainage system, the presence of vegetation, and seasonal damage (Talbot & Rahif, 2017). Regular geometric shapes such as roads are easily discernable on images and high-resolution

LiDAR, which can be used to provide information on widths, curve geometries, and slope (White et al., 2010). Similar to the in-field driving applications, Waga et al. (2020) used LiDAR-derived TWI models to predict road quality. They obtained an accuracy of up to 70 and 86% when the models were combined with other variables, such as surface quality index and soil type. Surface quality factors, including roughness, gradient, and camber, can also be recorded from a vehicle using a profilograph and then entered into the model to determine the effect of these factors on fuel consumption during timber hauling (Svenson & Fjeld, 2016).

27.3.2.2 Post-treatment Assessment of Disturbances

Harvest compliance in many jurisdictions includes minimizing rutting and damage to soils (Talbot & Rahif, 2017). Remote sensing can help locate and characterize ruts and assess the level of soil disturbance caused by an operation (Pierzchała et al., 2016). Haas et al. (2016) used photogrammetry to quantify variations in rutting related to tires of differing dimensions and the use of steel bands on forwarders. In a similar analysis, Marra et al. (2018) considered differences in tire pressure and the effect of several forwarder passes on rut development. Although this information is helpful at an individual rut level, remote sensing can also help locate and characterize ruts at the site level. Nevalainen et al. (2017) proposed a method for measuring rut depths from point clouds derived from images captured from a UAV. Talbot et al. (2018) used UAV-based orthomosaics to determine the extent and severity of rutting at a stand level and developed a method to reduce the need for field sampling in assessing site impacts. However, photogrammetry-based solutions have their limitations; for example, light and weather conditions can affect accuracy. Moreover, although surface models can be generated, occlusion greatly limits information related to site conditions for sites under a partial canopy or under brush mats on the ground.

27.4 Remote Sensing–Enabling Autonomy

The automation of the remote sensing information feed for active decision support and adaptive forest management is very close to reality. Embedded sensors that were used to remotely monitor hazardous or inaccessible environments (e.g., nuclear reactors or rail tracks) are being applied to the proximal monitoring of machine movements and perception of surrounding forest environments (Holmgren et al., 2019). SLAM, through onboard sensors such as 2D LiDAR scanners and stereo-cameras, has demonstrated its potential in estimating machine pose with reference to its complex unstructured forest surroundings either in combination with GPS (Pierzchała et al., 2018; Tang et al., 2015) or using only visual odometry in GPS-denied environments (Chandail & Vepakomma, 2020).

The last decade has seen a gradual paradigm shift toward developing "intelligent" machines converging with sensing systems, thereby moving from automation to autonomously navigating and negotiating different entities. In the aerial sector, miniaturized vision systems and artificial intelligence (AI) combined with remotely piloted systems or fully autonomous UAV swarms can now monitor and provide real-time situational awareness. For example, Hummingbird drones mounted with infrared-sensing instruments and AI are now used for fire monitoring (www.hummingbirddrones.ca). There is a movement away from man-heavy to man-light operations in manufacturing, agriculture, and mining sectors focusing on improving productivity or safety under challenging conditions. Although the forestry sector mandates environmentally friendly systems, the harsh diverse forest environment and obstacle-ridden forest floor may tax the limits and the reliability of all types of instruments (Billingsley et al., 2008). Although challenging to implement, the automation and autonomizing of future forestry is the focus of considerable research through programs, such as Forestry 4.0 (Canada, https://web.fpinnovations.ca/forest-operations-solutions-to-help-the-canadian-forest-industry/forestry-4-0/, https://www.youtube.com/watch?v=r4vhLQ8OEP0) or Auto2 (Sweden, Gelin et al., 2021), and the application of such programs to forestry issues (e.g., forest fire management, Sahal et al., 2021).

The success of any current or future forest management, particularly when dealing with triggered changes from extreme climate change–induced events, will require a prompt, timely, and reliable information feed. Remote sensing has been evolving, emerging, and converging with enabling technologies and offers reliable decision support and can ensure safer forest operations.

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