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Framework for near real-time forest inventory using multi source remote sensing data

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Forestry inventory update is a critical component of sustainable forest management, requiring both the spatially explicit identification of forest cover change and integration of sampled or modelled components like growth and regeneration. Contemporary inventory data demands are shifting, with an increased focus on accurate attribute estimation via the integration of advanced remote sensing data such as airborne laser scanning (ALS). Key challenges remain, however, on how to maintain and update these next-generation inventories as they age. Of particular interest is the identification of remotely sensed data that can be applied cost effectively, as well as establishing frameworks to integrate these data to update information on forest condition, predict future growth and yield, and integrate information that can guide forest management or silvicultural decisions such as thinning and harvesting prescriptions. The purpose of this article is to develop a conceptual framework for forestry inventory update, which is also known as the establishment of a 'living inventory'. The proposed framework contains the critical components of an inventory update including inventory and growth monitoring, change detection and error propagation. In the framework, we build on existing applications of ALS-derived enhanced inventories and integrate them with data from satellite constellations of free and open, analysis-ready moderate spatial resolution imagery. Based on a review of the current literature, our approach fits trajectories to chronosequences of pixel-level spectral index values to detect change. When stand-replacing change is detected, corresponding values of cell-level inventory attributes are reset and re-established based on an assigned growth curve. In the case of non–stand-replacing disturbances, cell estimates are modified based on predictive models developed between the degree of observed spectral change and relative changes in the inventory attributes. We propose that additional fine-scale data can be collected over the disturbed area, from sources such as CubeSats or remotely piloted airborne systems, and attributes updated based on these data sources. Cells not identified as undergoing change are assumed unchanged with cell-level growth curves used to increment inventory attributes. We conclude by discussing the impact of error propagation on the prediction of forest inventory attributes through the proposed near real-time framework, computing needs and integration of other available remote sensing data.

Introduction

The need for forest inventory updates

Forests are a dynamic ecosystem and resource, requiring managerial focus at multiple scales to effectively balance environmental and socio-economic sustainability. The development and maintenance of forest inventories is vital to sustainably manage current forest resources, as well as project their state into the future (Gillis and Leckie, 1996; Kangas and Maltamo, 2006; Tompalski *et al*., 2021a). As a result, forest inventories have a requirement for accurate, precise and spatially explicit information on the current state of forest resources (Kangas and Maltamo, 2006). In addition to remaining current and useful for management, forest inventory frameworks must undergo systematic and periodic updates to track changes in the forest resource, with respect to both management processes such as silvicultural treatment and harvesting and the impact of non-anthropogenic factors such as infestations, drought and fire.

In many countries, conventional forest inventory practice involves the combination of field measurements and aerial imagery (Leckie and Gillis, 1995). Following acquisition, images are processed to generate polygonal layers representing stands, within which attributes such as height or species composition are estimated. Ground sample measurements of tree or stand

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heights, species, volume, diameter at breast height (DBH) and stem density are then linked to the interpreted polygons to model other attributes of interest (Thompson *et al*., 2007). This forms the foundation of the initial (baseline) inventory. Forest attribute modelling over large areas enables understanding of the status of forest resources, providing information to drive silvicultural planning and improve stewardship practices for forest managers. Forests are, however, dynamic ecosystems and require routine data acquisition efforts for attribute estimates to remain timely, relevant and reliable. To address this, inventory frameworks must proactively address how, when and where updates will occur to maintain utility and data integrity.

Gillis and Leckie (1996) define inventory update as 'the process of detecting, collecting and adding changes to an inventory resulting from disturbances causing depletions (harvesting, fire, insect defoliation etc.), as well as changes to the forest causing accretions (growth, silviculture)'. The authors define two categories of data sources that can be used to update forest inventory: (1) changes that can be observed or mapped in a spatially explicit way such as harvest or fire and (2) changes that need to be sampled or modelled, like regeneration or growth.

Strategic inventories for example are designed to inform long-term forest management polices to characterize forest resources at the broadest spatial and temporal scale (White *et al*., 2016). As a result, broader spatial resolution and freely available data may be the most appropriate. Provision of wood supply is often the focus of inventories at the operational scale (Bourgeois *et al*., 2018), and such inventories thus require a combination of accurate tree attribute predictions at local to regional scales. Finally, operational inventories provide guidelines to allocate management activities to specific areas (Gautam *et al*., 2017) and thus fine spatial detail and high precision in predicting forest attributes are required.

Though strategies vary by jurisdiction, agencies often plan updates for inventory frameworks at regular intervals (e.g. every 10 years) to reflect changes from harvesting, natural disturbance, regeneration and growth. Depending on location and accessibility, inventory updates can be an onerous and expensive task. For example, difficult-to-access, remote forested areas still require ground sampling efforts for inventory estimates to remain as accurate as possible. These efforts in remote locations can incur high costs, often as high as several thousands of dollars to measure a single sample plot (Wulder *et al*., 2012b). To address these challenges, updates to inventory are often an ongoing process where operational areas are subdivided and specific areas are undertaken based on the necessity of data, and are updated incrementally.

Enhanced forest inventories

Conventionally, forest inventories are developed using a combination of field plots and interpretation of aerial imagery as a means to extend measurements over space (McRoberts and Tomppo, 2007; Tomppo *et al*., 2010). Despite the importance of aerial imagery for forest inventory needs, increasing challenges associated with deriving inventory information is becoming evident. First, trained soft-copy photo-interpretation has been commonly used to delineate stand boundaries and estimate species compositions; however, this process is labour intensive and costly, with a shortage of skilled interpreters becoming a reality (Goodbody *et al*., 2019; Holopainen *et al*., 2015). Second, inventory data demands are changing. Forest management is increasingly focusing on a broader range of ecological goods and services, with many attributes now requiring levels of detail that are not easily derived from previously utilized data sources (Goodbody *et al*., 2021). For example, attributes on below-canopy forest structure are challenging to derive although analytical innovations are developing (Jarron *et al*., 2020). Photo-interpretation is also largely limited to describing attributes at the stand level while operational-scale inventories may require information describing within-stand variation (e.g. Guay-Picard *et al*., 2015), or even individual tree attributes at a finer spatial resolution (e.g. Moreau *et al*., 2020). Furthermore, the accuracy of photo-interpreted attributes vary depending on the interpreter (Tompalski *et al*., 2021b), with a low probability of having a completely correct stand description (Leckie and Gillis, 1995).

Enhanced forest inventories (EFIs) have been proposed as tactical and operational forest inventory frameworks (White *et al*., 2016). EFIs are generated by integrating advanced remote sensing data such as airborne laser scanning (ALS) with ground sample data to develop predictive models of key forest attributes including height, basal area and volume (White *et al*., 2013). An immediate benefit of EFIs is that they include data—like ALS—that characterize the three-dimensional (3D) structure and variability of forest resources. These structural data are spatially explicit, providing summaries of best available estimates of forest height, cover and variability at the cell level (Goodbody *et al*., 2019). Unlike conventional polygonal inventories, EFI products are wall-to-wall raster layers of structural metrics, which can be directly included in modelling frameworks to provide high–spatial-resolution estimates of forest attributes (Tompalski *et al*., 2019). The value of data at the cell level cannot be overstated. Whereas conventional stand-level polygonal inventories provide single estimates of inventory attributes, EFI data provide fine-scale (i.e. 20- or 30-m cell size or 0.1 ha) estimates and variability within polygonal boundaries. Variation at the cell level provides a means to segment forested landscapes objectively using structural data.

A limitation of EFIs is that large costs are often associated with ALS data acquisition, processing, and inventory development. EFIs are anticipated to be performed at least every 10 years as a result of data shelf-life (McRoberts *et al*., 2018), similar to conventional inventory frameworks. This decadal time step leaves the opportunity for routine and frequent updating of the inventory between these significant EFI updates. Developments in near real-time inventory frameworks are needed to fill the gap between improving the information on yield and decreasing the lag since forest activities or disturbances. Avenues to integrate updates into inventory systems multiple times a year would likely improve spatial and empirical understandings of stand growth and development patterns, allow for more rapid and effective response to disturbance events, promote appropriate and tailored silvicultural prescriptions, develop refined economic projections of timber- and nontimber-values, improve understanding of socio-economic reliance on forest ecosystems and, ultimately, aid in formulating effective evidence-based forest policy. Studies have shown that the timeliness and accuracy of scheduled inventory updating can have a significant impact on management

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activities and affect the long-term future projections of forest and timber attributes. For example, McRoberts *et al*. (2018) found that regular updates to inventories helped reduce long-term inventory costs, as well as maintain the accuracy and applicability of data for predictive attribute models.

The key challenge is how to maintain and update EFI-derived inventories as they age. To address this, two main topics require consideration:

1. The availability and suitability of remotely sensed, geospatial and environmental data to regularly update EFIs must be explored and tested.

Many studies have proposed the use of various remote sensing datasets and platforms including optical satellite, aircraft-based and, most recently, remotely piloted aerial systems (RPAS; White *et al*., 2016). It is widely recognized that advanced remote sensing datasets can significantly improve the accuracy, precision and spatial extent of forest inventories (e.g. Tompalski *et al*., 2021a); however, objective workflows for how these data can be cost-effectively integrated into inventory framework are less clear. While the primary focus of this study, it is important to recognize that remote sensing data alone are not a universal solution. Field measurements and validation of remote sensing products will always be essential for ensuring reliability of inventory updates.

2. There must be a systematic framework to simultaneously update forest extent information in the event of disturbance, predict future growth and yield, and integrate information on forest management or silvicultural activities such as thinning and harvesting.

Assuming a combination of datasets can be utilized for inventory update, a critical component of the framework is considering which attributes within a forest inventory's large range should be updated, at what temporal frequency and how accuracy in change detection and reporting should be addressed and reported.

With these two fundamental concepts in mind, the purpose of this article is to develop the critical components of a conceptual forest inventory update framework, or living inventory, including inventory and growth monitoring, change detection and error propagation. In this article we conduct a review and propose that the increasing availability of finer spatial resolution remote sensing imagery at faster cadence provides a foundation where various data types can be integrated at multiple spatial and temporal scales to facilitate inventory update. We propose a near real-time forest inventory framework consisting of four major components: (1) a fine scale baseline EFI; (2) continuous change monitoring; (3) change analysis and reporting and (4) growth simulations.

In this article, to develop the underlying datasets and the proposed approach, we first review the range of data types proposed to drive the forest inventory framework. We then highlight the critical components of a forest inventory update framework including inventory and growth monitoring, change detection and error propagation. We then discuss the current limitations of the proposed framework, and conclude by discussing outstanding needs for real-time monitoring of actively managed forested areas. The review is laid out as follows: In the following section, we discuss changes in data availability and cadence which is driving the ability to increase inventory update cycles. We focus on increasing availability of satellite data—particularly those from virtual constellations—as well as the availability of CubeSat and RPAS. We also highlight the availability of 3D point-based datasets that allow accurate estimation of forest structure as derived from digital photogrammetry. In the next section, we propose the framework for the living inventory, describing each of the key aspects including detection and mapping of disturbances, and incorporate growth estimates. We then discuss how forest attributes within the inventory can be updated following either disturbance or growth. In the final section, we discuss additional considerations when developing an inventory update framework including error propagation, near real-time computation, additional datasets and resource requirements. Finally, we conclude with overall implications for forest management.

Changes in data availability and cadence drives potential for regular forest updates

Incorporating multiresolution, multisource remote sensing data can help inventories achieve numerous monitoring and updating goals. A wide range of remote sensing datasets can support forest inventory update with differing strengths and limitations (Table 1). These datasets vary in spatial and spectral characteristics, frequency of data acquisition and cost. In turn, defining their utility will then depend on strategic, tactical and operational inventory goals. In this section, we outline data types with potential for integration into the proposed framework, focusing primarily on their inventory update and monitoring potential rather than a one-time forest attribute estimation. The utility of other, potentially complementary, remote sensing data streams is discussed in later sections. Several comprehensive reviews have been written on the suitability of remote sensing data for forest updates, and we recommend these reviews to readers requiring a more detailed background on each (see the recommended literature in Table 1).

Satellite optical data for forest cover change

Moderate-resolution satellite imagery

Satellite imaging at landscape scales (moderate spatial resolution; 10–100 m) has been prevalent since the 1970s, allowing the development of long-term trajectories with which to calibrate change detection models. The Landsat satellite archive is the most widely used source of observations facilitating change detection (Gómez *et al*., 2016) and is the most defensible option to drive a change detection system for a number of key reasons. The archive dates back to 1972, with 30-m spatial resolution observations beginning in 1984. Consistent investment in the Landsat programme has facilitated continuous, uninterrupted global coverage derived from eight iterations of satellites, with future missions planned to ensure the future trajectory of the record (Wulder *et al*., 2019; Masek *et al*., 2020). Additional benefits of Landsat derivatives are their high quality and free

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Table 1 Selected characteristics of remote sensing data sources.

Data source	Scale/resolution	Update potential	Relevant literature	Cost
	Satellite optical data for forest cover change			
Moderate–spatial-resolution satellite imagery (e.g. Landsat 8, Sentinel-2)	10–30 m	Medium spatial resolution, moderate temporal resolution	(Phiri *et al*., 2020; White *et al*., 2017b; Zhu, 2017)	Free
High–spatial-resolution satellite imagery (e.g. PlanetScope, Spot 6&7, WorldView-3)	1–6 m	Targeted acquisitions for areas identified as change, strategic sampling tool	(Francini *et al*., 2020)	$/$$
	Aircraft-based data for 3D analysis			
ALS	<1 m Cell (e.g. 20 m) or individual tree level	Establishing the initial EFI; wall-to-wall or targeted EFI update	(Lim *et al*., 2003; White *et al*., 2013; White *et al*., 2017a)	$$$
Digital aerial photogrammetry	<1 m Cell (e.g. 20 m) or individual tree level	Wall-to-wall EFI update, requires prior ALS acquisition to establish ground reference	(Goodbody *et al*., 2019; Iglhaut *et al*., 2019)	$$
	Aircraft-based data for forest cover change			
RPAS	<1 m	Targeted acquisitions to provide detailed information on change	(Goodbody *et al*., 2017; Torresan *et al*., 2017)	$

availability, which have resulted in increasing data demand, as well as interest in development of algorithms with which to derive change (Wulder *et al*., 2012a). Finally, Landsat data are analysis-ready products (ARP), meaning that data are calibrated, atmospherically corrected and geometrically registered measurements of surface reflectance. This aspect of the data increase confidence that detections of change are being associated with the actual change on the land surface rather than originating from misregistration artefacts or atmospheric effects such as cloud and/or haze. As a result, any continuous change monitoring programme should utilize the Landsat archive as a primary data source.

The addition of Sentinel-2A and 2B imagery—launched in 2015 and 2017 respectively—offer an additional source of moderate spatial resolution imagery with similar spectral bands to Landsat, as well as additional complementary bands covering spectral regions like the red edge (705–783 nm; 865 nm), which are critical for vegetation assessment. Sentinel-2 has a spatial resolution of 10 m in some spectral bands, which is finer resolution than most of the bands on the current Landsat sensors. However, due to its launch in 2015, Sentinel-2 is unable to match the long temporal coverage available from the Landsat programme, thereby limiting the development of, for example, long-term spectral baselines. The temporal revisit of Sentinel 2A or 2B alone is 10 days; however, when data are used interchangeably, the repeat cycle can be reduced to 5 days, providing a dense time series. The relatively recent launch of the Sentinel-2 satellites is resulting in a rapid increase in research on the suitability of these data for forest cover assessment and change.

Passive optical satellite sensors are notable for their success for accurate and consistent detection of changes in forest area coverage (White *et al*., 2017a). While approaches for detecting stand replacing disturbances are well established, non–stand-replacing disturbances originating from disease, windthrow or insect outbreaks often result in lower reported confidence and are an ongoing area of development using this type of imagery. This is principally due to the variability in non–stand-replacing disturbances in a forest over space and time, as well as detection difficulties due to their often-subtle alterations to forest canopies and structure (Woods, 2004).

Senf *et al*. (2017) provide an in-depth review of the use of optical remote sensing data for insect disturbance characterization and advocated for the operationalization of near real-time monitoring of insect disturbances. Studies have indicated that bands in the shortwave part of the spectrum are particularly important because they can detect changes in leaf water content, leading to the discolouration of the foliage following disturbances such as drought (Moreno-Fernández *et al*., 2021) or bark beetle infestations (Ye *et al*., 2021). Changes in water content, and associated changes in spectral reflectance, are increasingly being monitored using time series data providing a means of detailing spatial and temporal disturbances associated with these non–stand-replacing disturbances. Not all changes will be intuitive, however, especially when monitoring for subtle changes in forest stands. For example, a non–stand-replacing disturbance which reduces tree canopy cover could result in an increase in understorey light and thus an increase in understorey vegetation productivity. This could lead to a corresponding increase in vegetation greenness at

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a pixel scale, rather than a decrease as would be anticipated with the disturbance. The ability therefore to track these small spatial scale, non–stand-replacing disturbances remains an active area of research and one for which additional study is needed. What is clearly needed, however, is an examination of the gradual spectral changes in a variety of spectral indices over time (de Beurs and Townsend, 2008; Eklundh *et al*., 2009; Spruce *et al*., 2011; Olsson *et al*., 2016).

Fine spatial resolution satellite imagery

Technological development has driven a rapid increase in the availability of high spatial resolution satellite imagery (<5 m), of which several platforms have successfully been used to support forest inventory updating and provide auxiliary data for the already delineated changes. Satellite sensors including WorldView-3, Pleiades or SPOT 6&7 are capable of providing multispectral imagery with spatial resolutions of 1.24 m (WorldView-3), 2 m (Pleiades) or 6 m (SPOT 6&7). The major drawback of these datasets is that they have a small coverage relative to moderate resolution satellite archives, are high cost to users and provide low temporal resolution. For example, in the case of Pleiades, the nominal revisit time is 26 days (nadir) with a swathe width of 20 km (compared to 185 km in the case of Landsat 8). To overcome the limitations associated with low temporal resolution, several of the existing high–spatial-resolution satellite sensors are deployed in constellations of two (e.g. Pleiades, Spot 6&7), five (e.g. recently decommissioned Rapideye) or even hundreds of satellites (PlanetScope). In addition, sensors can be shifted to oblique view angles with respect to the track to acquire off-nadir imagery. In the case of Pleiades, this reduced revisit time to 14 days (nadir, two satellites) or 4 days with a roll of 30°. However, changing view angles may correspond to subsequent changes in the utility of these data in a continuous monitoring framework. While spatial resolutions are high, the uptake of these datasets within forest inventory frameworks are largely limited by much higher costs, especially when multitemporal analysis are considered.

Compared to other high–spatial-resolution satellite imagery, the relatively lower cost and very high temporal resolution of PlanetScope imagery makes it a key source of data offering additional insight into recently disturbed areas of forest. PlanetScope consists of—at the time of preparing this manuscript—over 200 satellites that measure 10 × 10 × 30 cm and are equipped with a relatively simple four-band multispectral sensor, with plans for more spectral bands to come on future satellites. PlanetScope imagery is positioned on a lower orbit (400 km) and can be acquired with very short revisit times of 1 day and spatial resolutions of 3 m—all crucial characteristics for developing a near real-time forest inventory update framework (Francini *et al*., 2020; Leach *et al*., 2019). A drawback to these data, however, is that imagery is acquired using relatively inexpensive sensors. The focus of PlanetScope has largely been to produce a large quantity of satellites, resulting in lower spectral and radiometric data quality, which in turn challenges the output of consistent wall-to-wall mosaics (Leach *et al*., 2019). As a result, the current strength of PlanetScope imagery is in the ability to provide near real-time targeted acquisitions of areas undergoing change. When a change has been flagged at moderate-to-broad scales (Landsat, Sentinel), these data can be used to inform upon what drivers of that change might be, or how the forest ecosystem has been affected. Use of these high-resolution data to monitor disturbed areas through time also provides a means to understand and document how forests respond to change through time, a key component of inventory update. Investment and research to improve the spectral and radiometric resolution, quality, and consistency of these data is likely to result in a powerful and multipurpose dataset with large impacts in change detection and attribution frameworks.

Satellite constellations

One of the most significant developments in the delivery of Earth observation data for forest cover monitoring is the increasing use of satellite constellations. Satellite constellations have the ability to overcome the limitations of single sensors by recognizing that data from multiple concurrent sensors can be integrated and harmonized to produce a common data product (Wulder *et al*., 2015). Constellations can, in principle, result in data being combined from sensors with similar spatial, spectral, temporal and radiometric characteristics, allowing these data to be used as if they were acquired from one satellite system, with key benefits like increased temporal revisit. Indeed, the use of constellations instead of their component satellites reverses the negative relationship between temporal revisit times and spatial resolution (Figure 1).

The concept of satellite constellations is not new, with a number of Landsat satellites producing data concurrently during the 1990s and 2000s (Wulder *et al*., 2008b) and the NASA Terra and Aqua Earth observing satellites being designed to provide morning and afternoon overpasses producing identical products at an increased temporal resolution (Savtchenko *et al*., 2004). The last decade, however, has seen a much greater emphasis on satellite constellations. As discussed in a later section, the PlanetScope CubeSats form one of the most extensive constellations with over 200 individual satellites, acquiring imagery globally from identical platforms, allowing the constellation to acquire over 3 million km^2 of data daily, at a 3 m spatial resolution. Similarly, the European Space Agency (ESA) Sentinel 2A and 2B satellites are designed as a two-satellite constellation reducing the temporal resolution of a single satellite from 10 to 5 days under the same viewing conditions.

Building on the concept of constellations, a virtual constellation is where data are combined from sensor systems but not necessarily from the same family of satellites (Wulder *et al*., 2015). The most current example of a virtual constellation is the development of the harmonized Landsat sentinel (HLS; Claverie *et al*., 2018; Bolton *et al*., 2020) data series, which involves reprocessing both the Landsat 8 and Sentinel-2 satellite archives to produce a radiometrically, spectrally and spatially consistent global product at a 30 m spatial resolution. The temporal resolution of HLS is 2–3 days (Masek *et al*., 2022), and will potentially be further reduced once data from Landsat 9 (launched September 2021) and Sentinel-2C (scheduled to launch in 2023) are integrated into the product. While some of the benefits of the individual satellite datasets may be impacted—i.e. loss in spatial resolution or particular spectral bands of Sentinel-2—the result is a highly calibrated data stream

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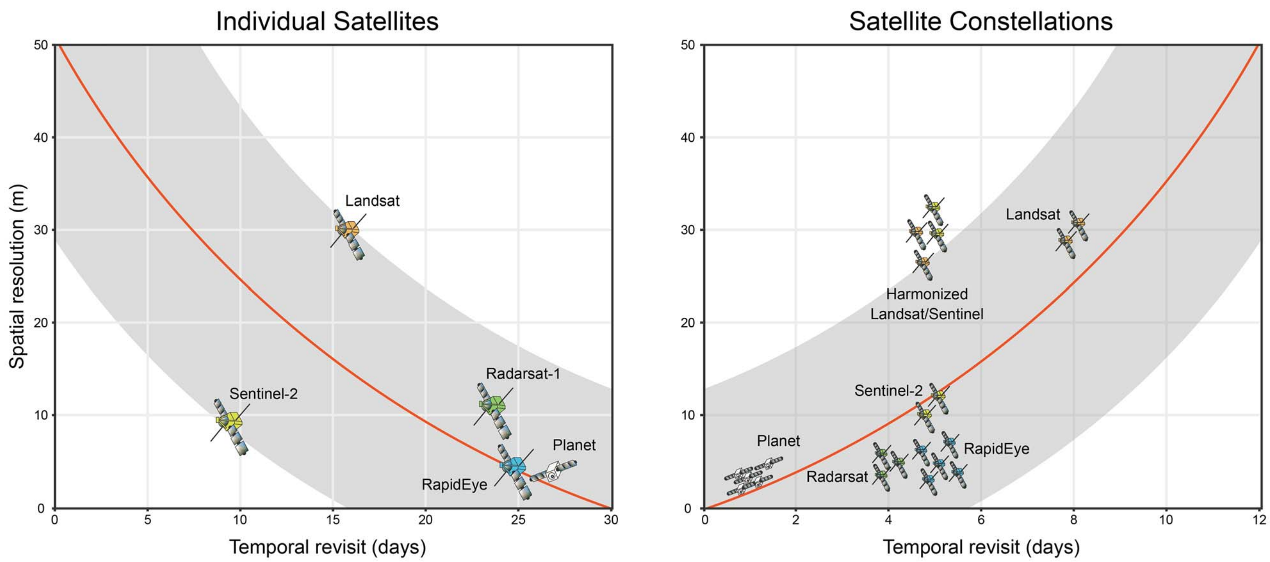

Figure 1 Relationship between temporal and spatial resolution for various remote sensing satellites (left) and their constellations (right).

with a temporal resolution much finer than individual satellite programmes alone.

Very high spatial resolution aircraft or RPAS imagery

As mentioned, aerial imagery has been the cornerstone dataset for forest inventory management, having remained integral to forest inventory workflows for decades (Zsilinszky, 1962). Routine and preplanned at regional or national levels, as part of government mapping initiatives (Goodbody *et al*., 2019), these data can be acquired as panchromatic, true-colour and infrared imagery. The use of stereo- and multi-image matching datasets—used to generate orthorectified imagery and mosaics—are common inputs for the interpretation of stand boundary delineation and species composition estimates (Leckie *et al*., 2003). This ability to acquire imagery and generate high-resolution mosaics at any time of the year facilitates 'on-demand' interpretation of resources for inventory purposes. The past 5 years have seen a significant increase in the use of RPAS to acquire high–spatial-resolution imagery and its subsequent use as an inventory and monitoring platform (Ivošević *et al*., 2015; Zhang *et al*., 2016). While limitations to the use of the platforms vary based on size, locale and intended use (Coops *et al*., 2019), they have become ubiquitous given their low cost, fast operationalization and the ability to acquire user-defined data at very high spatial resolutions (<10 cm). The benefits RPAS can provide for operational management tasks and inventory datasets are numerous. Firstly, their capacity to provide information on forest cover and change at stand and individual tree scales promote their use for enhancing managerial precision (Goodbody *et al*., 2017; Iglhaut *et al*., 2019). This is especially relevant in intensively managed stands, where harvest openings are often less than 5 ha in size, or in industrial tree-farm settings, where optimal harvest rotations for individual trees must be established to maximize profit. The ability to quickly deploy and acquire user-defined data in operational scenarios such as these provide a means of deriving individual tree- and stand-level wood procurement data routinely, helping to realize added value, improve cost savings and establish new value chains.

Aircraft-based data for 3D analysis

The use of ALS in forestry is recognized globally as mature, routinely being applied to forest management and operations (Næsset, 2002; Coops *et al*., 2004; Reutebuch *et al*., 2005; Wulder *et al*., 2008a; White *et al*., 2013) and critical for the generation of an EFI. While ALS is widely used in an area-based approach to forest inventories (Næsset, 2002), which is now operational in many jurisdictions (Woods *et al*., 2011; Næsset, 2015; White *et al*., 2016), its use as an update tool is less common. The use of high–spatial-resolution aircraft imagery has been spurred by the interest in image-based point clouds or digital aerial photogrammetry (DAP), which also facilitates accurate 3D representation of forest canopies (White *et al*., 2015; Goodbody *et al*., 2019; Iglhaut *et al*., 2019).

DAP utilizes automated photogrammetric approaches where pixels are matched on overlapping images and the vantage point of the camera to their location computed (Hirschmuller, 2005). Pixels are then mapped in 3D space in a point cloud which shares similarities to those acquired by ALS, however, pixels are used instead of directed light energy (White *et al*., 2015). The much lower cost of DAP data acquisition compared to ALS enables performing more frequent updates of forest inventory attributes with accuracies similar to when ALS point clouds are used (Hawryło *et al*., 2017). In addition, DAP data can be acquired from a wide variety of airborne platforms depending on information needs with both wall-to-wall datasets as well as targeted data acquisition over stands being possible. The flexibility of DAP to be acquired from a variety of platforms has seen DAP from RPAS an emerging field. Studies assessing the capacity for DAP data collected with RPAS to perform updating tasks such as Ali-Sisto and Packalen (2017) found that DAP was able to detect clearcuts

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with 98.6% accuracy, while thinning treatments were 24.1% accurate. Honkavaara *et al*. (2013) found that DAP was able to detect with 100% accuracy where more than 10 trees/ha fell as a result of storm conditions. These studies both indicate that DAP is capable of detecting major changes in forests, but may be less accurate in detecting minor changes to, for example, individual trees from a non-dominant canopy layer or changes to structure below the outer canopy surface.

A framework for near real-time forest inventory

A schematic diagram of the overall framework is shown in Figure 2. Critical to a near real-time forest inventory system is the requirement for an accurate and spatially exhaustive EFI upon which management actions, disturbances and growth can be synthesized. Typically, an EFI is derived on a regular grid (or raster) using statistical summaries of 3D point clouds, typically ALS data (White *et al*., 2016). Models are developed relating forest inventory attributes important for timber assessment to statistical summaries of the 3D point cloud (Bouvier *et al*., 2015; White *et al*., 2017a). Additional inventory attributes with known value for forest management such as cover stratified by vertical layers, primary and secondary structural variation and biomass estimates can also be computed to inform on forest ecosystem goods and services (Andrew *et al*., 2014; van Berkel *et al*., 2018; Frizzle *et al*., 2021). Using an EFI as a base in a real-time monitoring framework has numerous benefits:

- It is highly spatially detailed in a regularized grid that is commensurate with most moderate-resolution satellite imagery datasets.
- Models driving the EFI have known error budgets resulting from statistical models and ground validation plots.
- The modelling approaches and types of input datasets are somewhat flexible, meaning that an EFI can be tailored to the needs of the user.
- 3D data descriptions and field plot measurements enable modelling of multiple inventory attributes through time.
- The area-based approach to forest attribute estimation is supported by years of scientific research and offers accurate and detailed estimates of multiple forest attributes.

To update the EFI, different routines would need to be established depending on the disturbance type. In undisturbed pixels, forest attributes could be projected forward using existing growth simulators (e.g. Falkowski *et al*., 2010; Tompalski *et al*., 2018). After a stand-replacing disturbance (e.g. fire or harvesting) stand attributes would be reset and the area would be continuously monitored to assess the regeneration status. In case of non-stand-replacing disturbances, a link between a change in the spectral response and a change in the inventory attributes would need to be established. It is acknowledged, however, that not all attributes of interest can be accurately derived by the EFI methodology. Lack of multispectral response from ALS returns results in poor predictive ability to inform on tree species composition. As a result, information on species needs to be integrated into the EFI from a combination of existing polygon-level inventories, broader-scale species predictions from climatic and landform-based models, or by applying independent image classification routines using multispectral optical datasets.

ALS-based pixel-level EFI estimates of forest attributes represent the baseline condition (T_0). Updates to the baseline can then be integrated using a variety of remote sensing datasets detailed in Section 2. Across the entire forest estate, the framework is applied at the same grid resolution, either the same as the baseline EFI (e.g. 20 × 20 m), or is resampled to match the resolution of the core remote sensing data used to monitor changes (e.g. 30 × 30 m). It is also assumed that no change has occurred between the ALS data acquisition and the prediction of the EFI attributes.

Considering the characteristics of data used to monitor changes, described previously, as well as computational needs related to data processing, we propose a 14-day update cycle, although we recognize the exact update frequency can be adjusted by the user and will also depend on the availability of cloud-free observations. Based on available remote sensing datasets described in Section 2, we propose that HLS is used as the primary data to monitor and detect changes and every 14 days. Because the temporal resolution of the HLS data is 2–3 days, up to four images could be available during the 2-week period, depending on the cloud cover. Multiple algorithms are available to detect the change from a dense time series of spectral data including HLS data. In the following, we first propose an existing change detection algorithm to detect change within our near real-time inventory framework and then detail how additional remote sensing datasets and acquisition platforms could be integrated at varying spatial and inventory scales to update baseline EFI data.

Continuous monitoring and change detection

Changes in the spectral trajectory of individual pixels to date have most often been undertaken at annual time steps, using annual imagery composites (Hermosilla *et al*., 2015; Cohen *et al*., 2018; Griffiths *et al*., 2019; Corbane *et al*., 2020). These composites allow for a cloud-free image to be created and ensure that the influence of phenology is minimized using only images acquired within a predefined summer date range. While this produces cloud-free, high-quality image composites, it also limits the ability to assess seasonal variation or fine spatial changes occurring in the landscape due to the 30 m resolution.

A number of approaches have been developed to automate the detection of changes in forested landscapes (Kennedy *et al*., 2010; Hermosilla *et al*., 2015; White *et al*., 2017b; Cohen *et al*., 2018) using monthly, seasonal or annual change detection approaches. One well-established change detection technique designed for weekly or biweekly remote sensing observations is breaks For additive seasonal and trend (Verbesselt *et al*., 2010), which integrates the iterative decomposition of time series of remote sensing values into trend, seasonal and noise components. This allows the algorithm to change in the time series, without needing to select reference periods, thresholds or trajectories (Verbesselt *et al*., 2010). Zhu and Woodcock (2014) developed the continuous change detection and classification (CCDC)—an approach that uses all available Landsat data to move from annual to intra-annual forest

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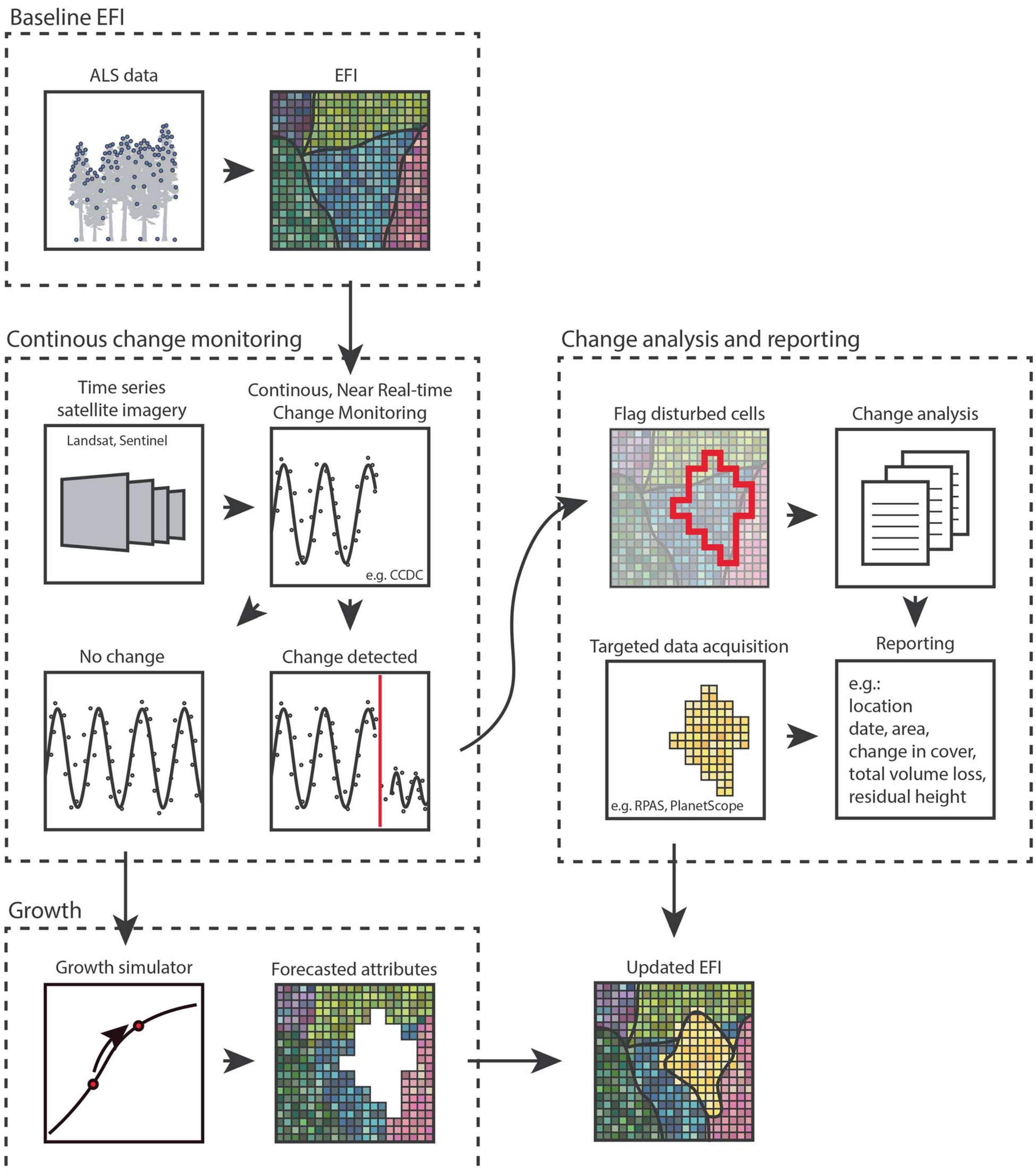

Figure 2 A schematic diagram of the proposed framework. After the generation of a baseline EFI (top), a time series of satellite imagery are used to monitor for change in near real time (left). If a change is detected (right), cells are flagged (red outline on top of grey background) for a targeted data acquisition. If no change is detected, then existing cells are forecast through time using growth models (bottom).

canopy cover monitoring. This was expanded upon in Zhu *et al.* (2020), in which a new algorithm, COntinuous monitoring of Land Disturbance (COLD) was presented that offers increased accuracy in change monitoring compared to CCDC. Zhao *et al.* (2019) demonstrated the efficacy of a Bayesian model averaging approach that can be used to detect changepoints and trends in spectral bands or indices while modelling and accounting for their seasonal variation. Attribution of the type and time of

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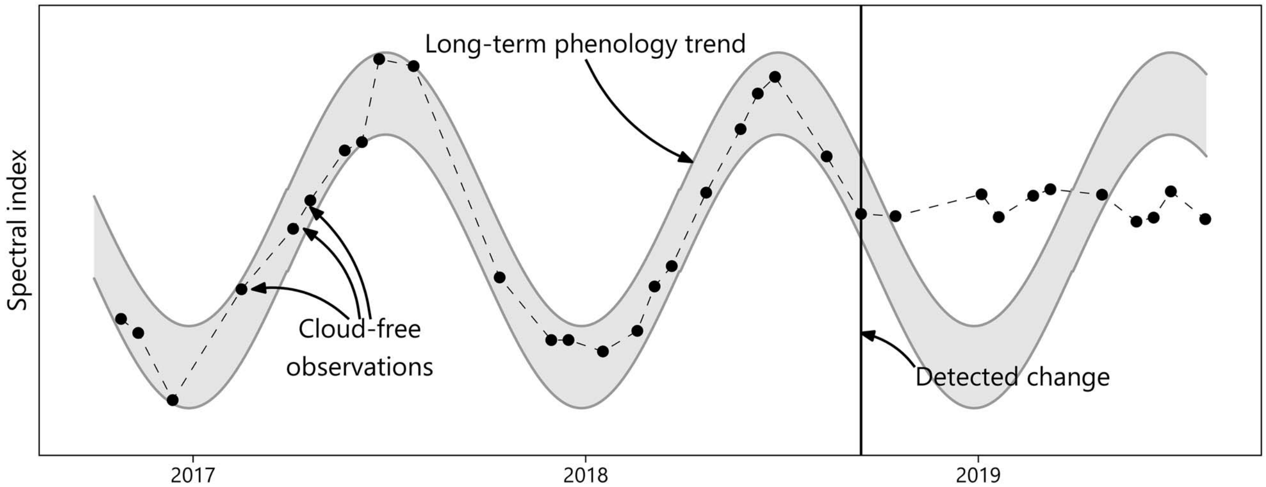

Figure 3 Conceptual diagram of the continuous change detection algorithm. For each pixel, a long-term phenology trend is derived based on the HLS record. Cloud-free observations are then analysed in near real time, and change is detected once the spectral trend does not match the historical trend.

change are invaluable to a change detection algorithm. While some algorithms are able to determine a change or no change, some are able to attribute the change to a specific disturbance type. For example, methods presented in Cardille *et al*. (2022) demonstrated that a multisensor time series of a single spectral index (such as the normalized burn ratio, NBR) can be used to determine the type and season of change. A change detection and monitoring algorithm based on kernel density estimates was developed in Decuyper *et al*. (2022), in which a probability of change is associated with pixels of interest based on deviations from a reference frequency distribution.

In these and other approaches, rather than using a single image, or image composite per year, each pixel is assumed to have an underlying periodic behaviour associated with phenological vegetation patterns. By fitting trajectories to chronosequences of pixel-level spectral index values, the algorithms learn the behaviour of each pixel through a training period and then detects deviations from those seasonal patterns over time (Figure 3). For example, a deciduous stand will have a highly pronounced pattern in its spectral trajectories associated with leaf-on and leaf-off conditions (White *et al*., 2017b). Should the stand ultimately be harvested, index values for a particular pixel will follow these sinusoidal patterns until a disturbance event and then deviate. The degree to which the pixel deviates from the periodic phenological pattern can provide detail into the type of change, and consequent land cover of that individual pixel (Figure 3). Though coniferous stands have less pronounced seasonal dynamics, slight sinusoidal pattern behaviour can be observed and modelled using this approach as well (Seyednasrollah *et al*., 2021).

Based on the review, we would propose that a forest inventory update system be designed to be undertaken at a spatial resolution which matches the EFI grid cell size with the desired HLS spatial resolution. Spectral bands (covering 400–2500 nm) or indices from HLS, can then be fitted using a change detection algorithm to flag forest disturbances. If the algorithm detects a significant deviation of the trajectories of the spectral bands or indices at a given time step, the cell is flagged as changed.

Stand-replacing disturbance

In the case of a stand replacing disturbance, deviation from the anticipated unchanged spectral response in a single spectral channel (short-wave infrared) with a fixed threshold is sufficient to detect change (Zhu *et al*., 2012). The intensity of the disturbance event, which has resulted in the pixel being flagged, can be assessed by analysing the degree of change in the spectral value. In the simplest case, if the change in short-wave infrared reflectance exceeds a large predefined threshold, then a complete removal of vegetation could be assumed to have occurred (i.e. a clear-cut harvest) and the pixel would be reset to a non-vegetated state, awaiting a trigger to commence regeneration at a later date. Zhu and Woodcock (2014) demonstrated that the threshold for a change event such as a stand-replacing disturbance can be based on the RMSE of the fit of the trajectory to the time series. If the spectral signal deviates from model prediction by more than three times the RMSE, then a change has occurred. The spectral value in subsequent time steps can also be monitored to validate the change to ensure it was not due to noise or other perturbation in the spectral response.

Non–stand-replacing disturbances

We anticipate lesser magnitudes of reflectance change for non–stand-replacing disturbances such as insect infestation, drought or silvicultural treatment such as thinning compared to those associated with the complete removal of vegetation (Coops *et al*., 2020). Pixels with lesser deviations from the anticipated trend would need to be monitored for a series of additional time steps to validate, and likely to have lasting impacts on the forest stand. Monitoring the spectral trajectories over time, after the initial deviation, would increase confidence in the detection of

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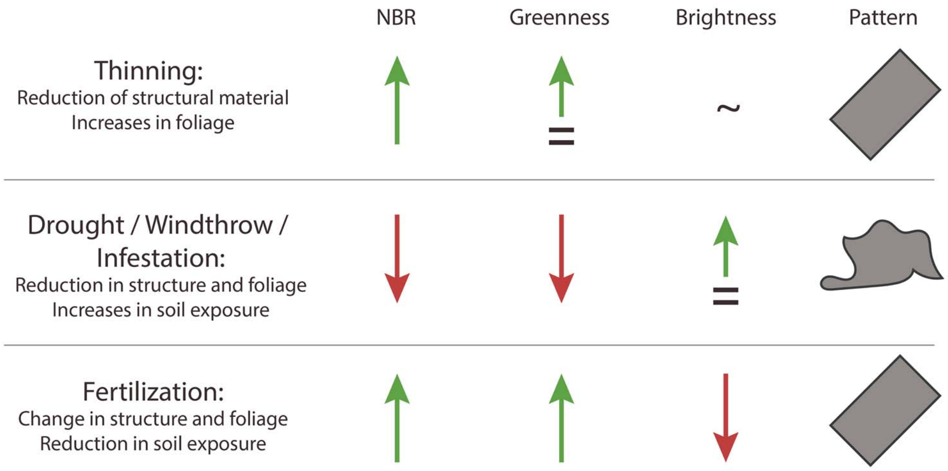

Figure 4 Theoretical response of NBR, greenness and brightness to different non–stand-replacing disturbances. Also depicted is a typical spatial pattern (natural or anthropogenic) of those disturbances. In the figure, 'Thinning' refers to precommercial thinning, wherein the timber value of removed trees is low. In the 'Pattern' column, anthropogenically derived boundaries are represented by rectangles while geometric shapes represent those not directly associated with anthropogenic drivers.

the disturbance as well as help discriminate amongst disturbance agents (Senf *et al*., 2017). Explicit separation of disturbance types could be performed through monitoring the magnitude of change and spectral signature of change via the use of spectral indices such as the NBR, greenness indices such as the normalized difference vegetation index (NDVI), enhanced vegetation index (EVI) or the Tasseled Cap greenness component, and a spectral index which has been shown to be sensitive to exposed soil such as Tasseled Cap Brightness (Goodwin *et al*., 2008; Meigs *et al*., 2015). These indices in combination with spectral bands can provide an initial determination on the most likely non–stand-replacing disturbance agent occurring in the stand. An example of the logic is shown in Figure 4 below.

Spatial arrangements of flagged pixels can be assessed to examine whether a pixel is isolated in a group of otherwise unchanged pixels, or if there are spatial clusters of pixels flagged as undergoing change. If a spatial cluster is apparent, it can be clustered and attributes on the size and shape of the disturbance calculated to inform the type of change. The characteristics of these objects can also be monitored over time to help infer information on change (Kennedy *et al*., 2012). Previous research has clearly shown that harvesting operations are more likely to occur in regular-sized polygons of particular size, commensurate with the forest management policy at the time (Hermosilla *et al*., 2018). In contrast, forest fires are likely to result in a patchier disturbance of varying severities and different sizes (San-Miguel *et al*., 2017). In the case of insect infestations, the change may occur in small clusters of pixels which would be associated with small-scale outbreaks, or much larger areas which could be indicative of broader scale infestation events. The timing within the year of detected change can also be informative on the type of change occurring. While Figure 4 demonstrates theoretical changes for single, discrete disturbance events, it should be noted that multiple non–stand-replacing disturbances could occur at approximately the same time, as disturbance agents such as insects, drought and blowdown can be linked (Senf *et al*., 2016, 2017; Seidl and Rammer, 2017). In these cases, the spectral signatures of disturbance may be mixed and additional work to separate the types of disturbance may be needed.

Fine-scale analysis of disturbed pixels

Additional fine-scale remote sensing datasets can be used to ascertain the exact cause of the change and the implications on the condition of the forest stand. These are targeted acquisitions over areas of change where finer scale satellite imagery such as PlanetScope or targeted aircraft and RPAS acquisitions come into play (Figure 5). The temporal resolution of PlanetScope constellation data would allow forest managers to quickly observe an area flagged as change in order to detect the finer scale patterns of the disturbance (Figure 6). While this imagery is typically not of sufficient radiometric quality to be utilized through an automatic change detection routine, single-image datasets are still valuable in identifying change drivers as quickly as possible and giving estimates of change attributes. A number of processing pipelines have been developed to automatically coregister and radiometrically normalize temporally dense series of PlanetScope data (Leach *et al*., 2019). Such time series could be used to quantify and map changes in stand attributes after a disturbance is detected using HLS. As the constellation is regularly acquiring imagery, continued data access—allowing managers to leverage localized areas on a user request basis (thus being cost effective)—would ensure that imagery could be viewed within a short period of a detected disturbance. In the case of acquiring a fine temporal sequence of high–spatial-resolution satellite data to resolve this change, the focus should be on assessment of changes in canopy cover, given the 2D nature of the acquired imagery.

In the cases where information on change in vegetation structure is of interest, aircraft-based data acquisition may be better suited than optical satellite data. Depending on the size of the

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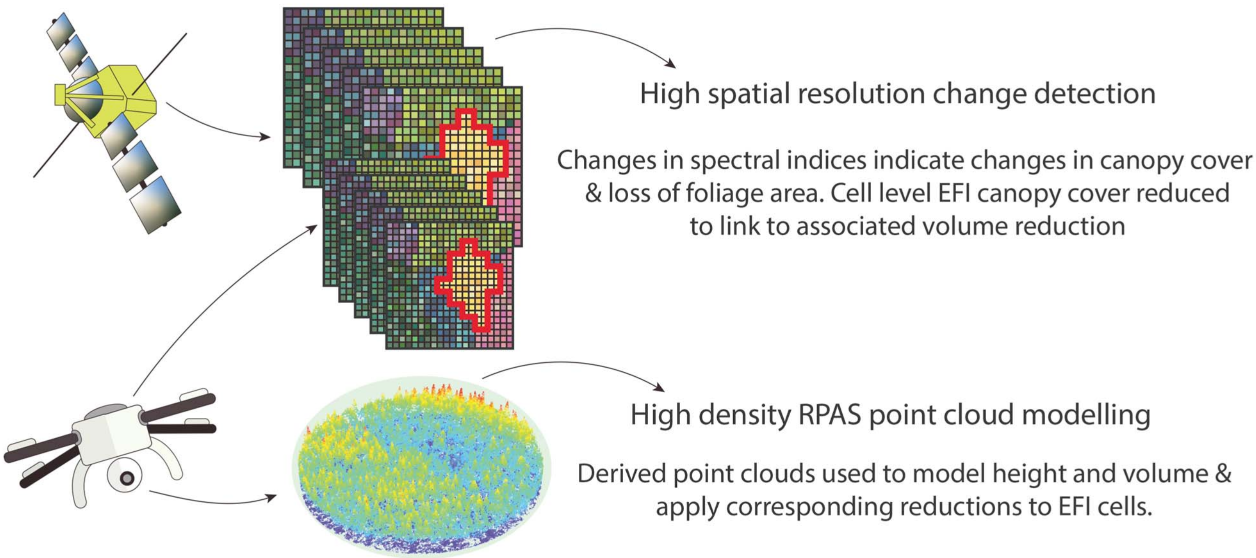

Figure 5 Additional fine-scale remote sensing datasets can be used to detect both changes in land cover, such as harvest or fire or changes in 3D structure using high-density RPAS point clouds.

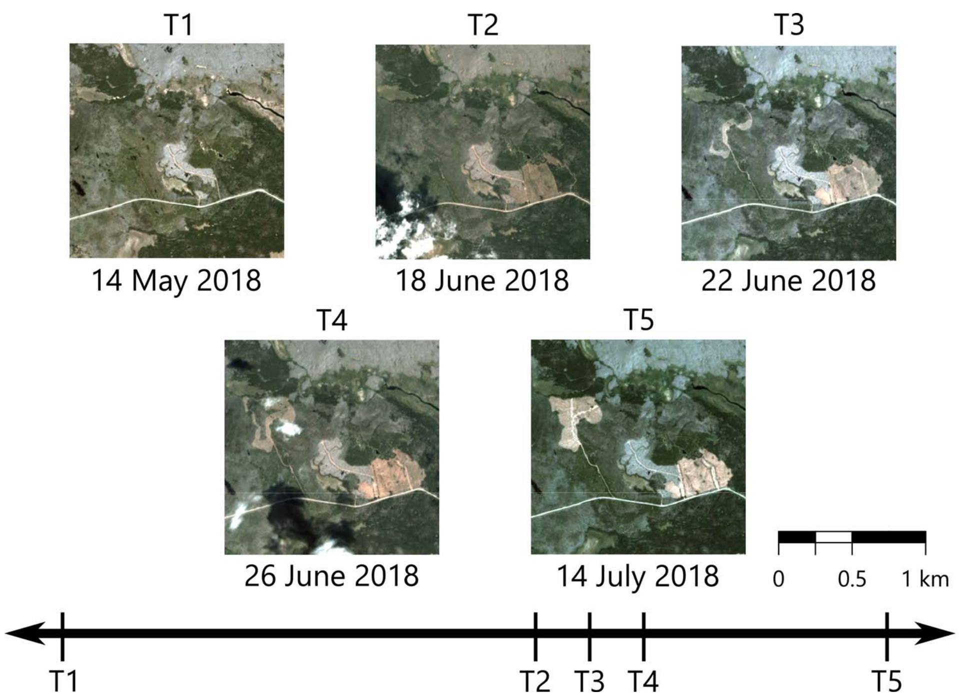

Figure 6 An example of using high-spatial-resolution satellite imagery for fine-scale interpretation of disturbance. In this example, PlanetScope imagery is used to observe a series of harvests near Quesnel, British Columbia, Canada.

disturbed area, a range of different acquisition campaigns could be developed. For large disturbances, collecting data on the entire area may not be realistic. In such scenarios, the area flagged as change could be stratified, for example by the severity of the disturbance or species composition. Airborne imagery could then be acquired on targeted transects allowing for manual interpretation to detect foliage discolouration or predict changes in foliage area and amount. ALS or DAP acquisitions to quantify changes in stand or individual tree structure like height and cover associated with the disturbance are also feasible within cost constraints. By comparing these estimates with the most recent EFI, a severity of change could also be determined. While the cost of performing an update with an aircraft may be costly (particularly across large areas), we expect that as RPAS technology becomes

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more mature that the ability to acquire user-specified data over disturbances will become more automated and less limited by flight times.

In the case of smaller disturbances, for example, across several forest compartments, RPAS could be deployed to acquire data. Orthophoto and DAP point clouds could be used to perform detailed characterization of changes, either through manual interpretation or based on automated processing routines (Arkin *et al*., 2019). Much like ALS acquisitions, RPAS-derived DAP data could play a valuable role in updating EFI estimates. High correlations between upper height percentiles for ALS and DAP could enable transferability between the two datasets (Tompalski *et al*., 2019), allow for reducing or eliminating the need to collect field data required for model calibration and help to automate attribute estimation post-disturbance. Prior knowledge of the relationships between ALS and DAP metrics included within models is fundamental to this process. High-density DAP point clouds derived from RPAS imagery would improve understanding of the impacts of non–stand-replacing disturbances. Further, accretions in forest attributes (e.g. increase in canopy cover) could help forest managers assess silvicultural interventions such as fertilization. Goodbody *et al*. (2017) demonstrated that an RPAS data acquisition over a selectively harvested area could produce accurate data with which to update the corresponding EFI. To do so, DAP point clouds acquired using RPAS were used to estimate individual tree height and volume increments. Individual trees were detected from RPAS DAP canopy height models (CHMs) and mean tree growth assessed from the change in CHMs. Similarly, mean gross tree volume increments were computed over the time period. We do recognize however that RPAS, while relatively straight forward to conceptualize how these fine-scale, targeted datasets can be used to detect and validate forest cover change, the reality is that there can be significant costs involved in operating RPAS in a forest management programme. For example, prices vary depending on the level of accuracy and automation of the RPAS and the type of sensors deployed. Operator training is required, and in some cases additional training is needed if RPAS are to be flown near populated areas. Operational constraints around where users can fly and battery life also limit the area that these instruments can cover. As a result, the overall cost in utilizing RPAS in this framework should certainly be recognized as more than simply the cost of the RPAS unit itself.

Incorporating growth

Incorporating growth into the inventory is the third key component of the framework (Figure 2). EFI cells unflagged for change following the continuous monitoring module are assumed to be growing within the 14-day observation period, and stand attributes in each of the 20 × 20 m cells are adjusted based on the available growth model, operating on an annual time step (Figure 2). Individual growth curves assigned to each cell can be used to increment height and volume (Tompalski *et al*., 2021a). Changes in canopy cover over time are less likely to be included in the growth model, so subsequent changes in spectral bands or a greenness index can be used to update cell-level estimates (Andela *et al*., 2013; Hansen *et al*., 2008).

Several techniques have been proposed to link raster-based EFIs to forest growth models. These approaches can either utilize tree- or stand-level growth models depending on existing forest industry practices and growth model design (Lamb *et al*., 2018; Tompalski *et al*., 2018). Using an area-based EFI, estimates of volume, stocking density, DBH and height can be linked into a stand growth model, assuming species information can be derived from the existing inventory (Tompalski *et al*., 2016). In the case of a tree-level growth model, tree lists would need to be inferred within each EFI cell in order to allow the model to predict tree growth (Lamb *et al*., 2018).

Utilizing growth curves on a cell-by-cell basis derived from historical forest biometric information can be problematic in the context of changing biogeoclimatic conditions. Research into adaptive approaches for deriving growth estimates are therefore needed. One such area is the use of simple physiological models which utilize information on rainfall, temperature and sunlight to predict stand growth over time. Conventionally, physiological growth models (e.g. 3PG, Coops *et al*., 1998; Landsberg and Waring, 1997) have been derived for large terrestrial areas and biomes, however, with increased availability of fine-scale information on climate and terrain, much finer scale spatial predictions of forest growth models are now possible (Coops and Waring, 2001; Tickle *et al*., 2001). As a result, a climate-driven forest growth model could be developed for given species and management scenarios, and replace existing models based on historical growth patterns alone.

Updating EFI attributes following disturbance detection

HLS-based continuous change monitoring should allow for timely and accurate detection of disturbed areas and inform on the disturbance type, area, severity and other disturbance-specific characteristics (Claverie *et al*., 2018; Chen *et al*., 2021; Wulder *et al*., 2021). Additional approaches are needed, however, to translate and integrate detected changes in spectral properties into changes in EFI attributes. This final component of the framework depends on the disturbance type, inventory attribute and availability of additional data acquired after the disturbance. In the simplest case of stand-replacing disturbances such as clear-cut harvesting, the majority of EFI attributes (such as tree height, volume and stocking) can be reset to 0. Rules for non–stand-replacing disturbances will be more challenging to create and implement (Senf *et al*., 2017). Once disturbances have been detected, the framework can be used to assess the recovery of disturbed areas in terms of the changes in associated attributes such as height or stem density. However, under changing climatic and management conditions, baseline assumptions that the type and amount of vegetation regeneration (i.e. species composition, density, health) is consistent with what was present before may not be valid. As a result, any ongoing assessment of a post-disturbance stand should be designed to be sensitive to a variety of regeneration pathways (e.g. successful regeneration vs invasive species dominance) not only for monitoring purposes but also to assist silviculture decision making and facilitate the planning of interventions as necessary.

Fine-scale data collection

To perform an update of EFI attributes, one potential scenario is to collect additional fine-scale data over the disturbed area to

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facilitate greater accuracy of the updated attributes. These data can include targeted field measurements, high-resolution satellite imagery (e.g. PlanetScope), DAP data acquired with RPAS or, in the case of large disturbances, ALS data acquired over transects. In the case of updating with comparable 3D point cloud datasets (both DAP and ALS), several of the EFI attributes may be updated directly, without the need of developing or applying predictive models. Specifically, canopy cover, stem density and height may be inferred directly from the point cloud. Alternatively, existing models (e.g. developed for the EFI at T_0) can be applied to estimate all of the inventory attributes, including basal area and volume. However, existing studies have shown that such model transfer often results in biased estimates (Tompalski *et al.*, 2019; van Ewijk *et al.*, 2020). In such cases, additional data collected in the field would allow to calibrate the models and result in unbiased estimates.

Relating spectral indices to changes in EFI attributes

In another scenario, predictive models can be developed by comparing variation in pairs of EFI attributes to coincident changes in HLS-derived spectral predictors (Figure 7). As the expected level of accuracy of the estimated inventory attributes derived with the developed models is lower than the accuracy of the EFI predictions, instead of modelling the absolute attribute values, the models can be designed to estimate their change. To do so, the initial 20m EFI cells would be stratified by attributes such as species composition, age, or productivity, depending on data availability. Within each strata, pixels would then be grouped in pairs (groups of all cells within a strata matched across a single time step). For each pair, differences in spectral attributes (e.g. difference in the near- and short-wave infrared bands, as well as tracked spectral indices), and differences in EFI attributes would be calculated. This would allow a library to be established of the differences in inventory attributes and the corresponding difference in spectral values. A model would then be applied to estimate the relative change in EFI attributes, by strata, when a non–stand-replacing disturbance is detected. A k Nearest Neighbour (kNN) approach based on the change in spectral value of the detected disturbance would be beneficial in this scenario as it would allow all EFI attributes to be adjusted up or down simultaneously. An initial examination of the approach using available ALS data from eastern Canada involved developing an EFI of key attributes using the area-based approach. Raster estimates were then merged with Landsat-derived spectral indices (NDVI, EVI). Stands were then stratified according to species composition, age and site productivity class, and within each strata all pixels were paired, with differences for each pair calculated for EFI and spectral values. Initial results demonstrated that using kNN with a random forest-based distance metric produced models capable of imputing change in stand attributes based on change in spectral values.

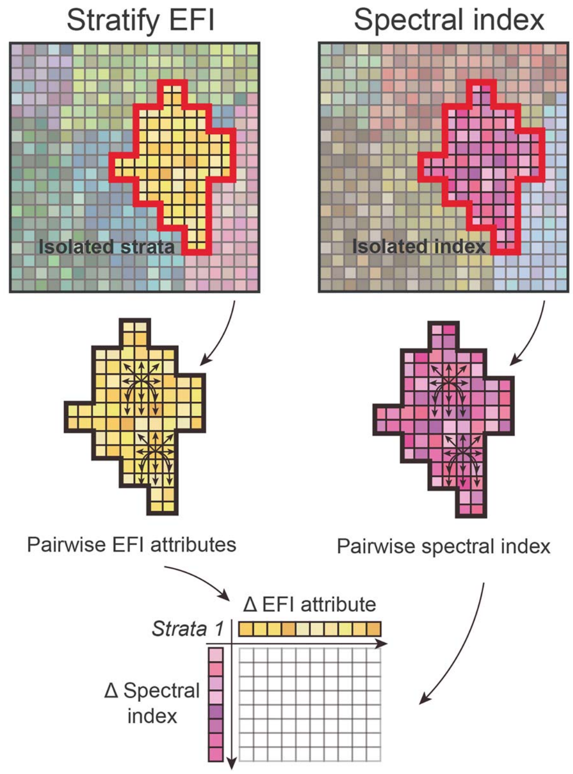

Figure 7 Schematic diagram of how a change look-up table could be developed to relate strata-level variations in spectral indices to reductions in forest inventory attributes.

Implementation considerations

Error propagation

Understanding the impact of error on the prediction of forest inventory attributes through the living inventory framework is critically important in order to ensure that attributes are predicted reliably. As discussed throughout, the backbone of the framework is a regular EFI, which could occur every 5–10 years over a given forest management area. We envision that forest attributes would be predicted at each of these times using periodic ALS acquisitions and that field programmes would be instigated in order to develop and validate attribute prediction. As a result, every time a new wall-to-wall EFI is developed, the derived estimates of forest attributes will have associated error estimates. Previous research has demonstrated that the relative RMSE of height, DBH, basal area, volume is typically between 10 and 30%, with the highest accuracy corresponding to estimates of height (Wulder *et al.*, 2008b; White *et al.*, 2016; Roussel *et al.*, 2017; Goodbody *et al.*, 2019).

The inclusion of periodic update information should be seen as an update to the EFI values rather than a recalculation of absolute values at each time step. In other words, EFI-predicted attributes could be either increased or decreased based on these periodic update observations. For example, based on past research, the majority of inventory attributes derived using DAP would have similar or slightly lower accuracy than that of the initial EFI (Goodbody *et al.*, 2019). This accuracy does, however, depend on a multitude of factors related to the dataset itself, as well as the attribute of interest. While some attributes can be estimated directly from the point cloud with relatively high accuracy (e.g. height, canopy cover), some require a predictive model to be developed first (e.g. basal area, volume) or could

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be supplemented with limited amounts of field data. In such cases, either a field reference would need to be collected to facilitate developing new models or an existing model developed for the original EFI could be applied. The latter case (model transferability) allows to markedly lower the cost of deriving the estimates, however may pose a risk of significant bias (Tompalski *et al*., 2019; van Ewijk *et al*., 2020). A third approach, based on linking changes in volume or basal area with changes in height and cover could be developed and applied (Mitchell *et al*., 2017). As a result, estimates of attributes that require modelling would be modified based on attributes estimated with different remote sensing data sources.

In the case of growth model estimates, the fitting of the growth curve to the annual observations in time has been demonstrated to be impacted by the number of ALS observations through the time sequence. Establishing which growth curve is appropriate for each EFI cell using a single EFI estimate of volume, height and DBH will result in lower accuracy than when more estimates are used (Tompalski *et al*., 2018). As a result, as the near real-time framework is applied over time and additional ALS datasets are acquired, growth estimates for each individual cell based on growth curves either derived statistically or physiologically would improve.

The near real-time 'time step'

When applying the near real-time framework to a forested area, it is important to recognize that the appropriate definition of 'near real-time' will likely vary. Utilizing a calibrated change detection algorithm in near real-time requires the regular availability of analysis-ready remotely sensed imagery (such as HLS data products). The latency between a Landsat overpass and the availability of ARP from that overpass, is approximately 1 day (Gorelick *et al*., 2017). The HLS product version 2.0 is intended to continually update the available Sentinel-2 and Landsat 8 imagery with less than 2-day latency (Masek *et al*., 2022). Furthermore, continuous change detection algorithms require multiple observations to reliably detect a disturbance (at least six in the case of COLD; Zhu *et al*., 2020). Considering the temporal resolution of the HLS product, latency and the number of required images, approximately 14–20 days would elapse before the COLD algorithm would automatically flag a pixel as changed, provided all images were free of clouds, shadow and snow.

The use of the HLS markedly increases the probability of obtaining a cloud-free image for a region of interest. For a continuous monitoring framework reliant on optical data, the accuracy and timeliness of change detection would be hindered in areas of high cloud cover or prolonged snow as these pixels are commonly masked out of resulting algorithms (Zhu and Woodcock, 2014). For example, persistent clouds in tropical or coastal areas, or persistent snow in high latitudes, would limit the number of valid observations during a given time period, potentially reducing the capacity of a change detection algorithm to establish the initial long-term phenological trends or to detect change in a timely manner. In these cases, the temporal update would need to be extended. Even with the temporal resolution of 2–3 days, periods of no data availability due to consistent cloud cover may occur and may last for several weeks, or several months in the case of persistent snow or ice.

The use of finer spatial resolution data to investigate change once it is flagged requires much shorter time as the imagery from for example PlanetScope is often available within 24 h of acquisition. Manual interpretation of areas of change could therefore be interpreted within a day. More complex analysis requiring additional processing would certainly increase this time. Should airborne imagery either from aircraft or from RPAS be required to sample or spatially cover disturbance events such as harvesting or fire, the timescale would be dependent on aircraft or RPAS availability, weather conditions, surface conditions and other factors. Most probably a start of RPAS data collection would require more than a week of pixels being flagged as change from the near real-time framework. However, while we have specified a particular configuration of this real-time inventory framework in this article, we acknowledge that it could be modified depending on a number of factors related to the purpose of the forest inventory itself. In this article, we have discussed the application of the framework to be responsive to harvesting, silviculture and other precision forestry operations which would require fine spatial detail as well as high temporal fidelity as the decisions made from the framework would be used along the entire supply chain to inform upon harvesting and ultimately timber value.

Use of other datasets for temporal update

The proposed framework incorporates a subset of the available remote sensing imagery archives. Opportunities for other datasets could be utilized in this framework should be fully explored. Data fusion could be considered, which would allow, for example, satellite-based synthetic aperture radar (SAR) or interferometric SAR to be used which have been used to inform predictions of forest attributes (Mitchell *et al*., 2017). Across a variety of studies, L-band SAR has been the most used and is available as a global coverage from the phased array-type L-band synthetic aperture radar system onboard the Japanese-Advanced Land Observing satellite (ALOS). L-band SAR, with its longer wavelength, has been shown to be more sensitive to changes in biomass (Coops, 2002), especially at higher quantities. Currently ALOS-2 imagery is producing annual 10-m spatial resolution mosaics with increased temporal resolution in tropical regions for forest and wetlands monitoring (Rosenqvist *et al*., 2014). Future campaigns, such as the National Aeronautics Space Administration - Indian Space Research Organisation Synthetic Aperture RADAR (Radio Detection and Ranging) (NISAR) mission, will allow global SAR observations with very high temporal repetition (Rosen *et al*., 2015).

The shorter wavelength C-band SAR data which, while being more commonly available from both RADARSAT and Sentinel-1 satellites, has cost, temporal acquisition parameters and saturation issues which often limit detailed temporal observation and limited examples in forest monitoring. X-band RADAR has also been used, acquired from the Tandem-X mission which provides elevation information as well as insights into the quantity (and height) of forest vegetation when compared to conventionally derived digital elevation models (Hyde *et al*., 2006). The advent of sample-based lidar from spaceborne platforms including Global Ecosystem Dynamics Investigation (GEDI) on the International Space Station and Ice Cloud and land Elevation Satellite (ICESAT)-2 offers intriguing possibilities of how these sample-

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based updates could be incorporated into the framework. While this has not been developed in this article, a sampling framework which would allow overall estimates of change in particular growth to be monitored using regular samples of space-borne lidar could offer an alternative to relying solely on growth models to predict growth.

If the forest inventory is designed to monitor other ecological goods and services beyond timber, for example inventory programmes in unmanaged forest areas where production is not the primary driver of forest management, then both the temporal update and the spatial scale of the framework could be altered. Temporal updates could happen three or two times a year to coincide with major seasonal updates and the spatial resolution could be coarsened to allow for potentially more cost-effective imagery solutions with respect to data acquisition. In this respect, especially over large areas of unmanaged forest, the MODIS sensor onboard Terra and Aqua satellites with daily between 250 m and 1 km resolution imagery since the year 2000 offers the most cost-effective solution. Application of MODIS imagery has proved particularly useful in near real-time monitoring of fire (Roy *et al*., 2005), drought (Verbesselt *et al*., 2012) and pest and insect infestations (Spruce *et al*., 2011). Much of this analysis has been retrospective or used to quantify change in forest conditions at a landscape scale at annual or decadal time steps (Xin *et al*., 2013). However, in the case of forest inventory update, a clear disadvantage of the MODIS datasets is their coarse spatial resolution, with many forest cover changes occurring at much finer spatial scales and as a result, a reliance on MODIS imagery data alone to detect and characterize fine-scale forest cover change will result in low detection rates at the tactical or operational scale.

Computation needs

While many of the datasets that have been proposed to be used within the framework are provided in an analysis-ready format, we acknowledge that the computing power and technical capacity of the users to apply the framework is still high. It is unlikely in these initial stages of deployment that the framework could be applied by local forest managers and that a high degree of processing capability and coding may be needed to establish this framework and ensure its accuracy at least in the short term by remote sensing professionals. As these frameworks become more common and data providers are more regularly producing ARP, then the framework could be applied more easily to forest focus sites without the need for such technical skill.

Implications for management

Forest management in the 21st century faces changing information needs, resource demands and pressure on landbases (Messier *et al*., 2015; D'Amato *et al*., 2018; Hagerman and Pelai, 2018; Achim *et al*., 2021). The living inventory framework outlined above is proposed to address these challenges. The successes highlighted in the reviewed literature should provide a mechanism by which forest managers can combine EFI forest attributes with an update process, driven by satellite data. Under the proposed framework, forest managers will have access to refined, detailed, and timely information upon which they could rely to make management interventions and develop operational planning (Puettmann, 2011; O'Hara and Ramage, 2013). Additionally, managers will have an expanded capacity to apply remediation measures after disturbances, thereby reducing resource losses (Senf *et al*., 2017).

In the first phase of the near real-time monitoring framework where high cadence satellite optical data flags disturbances, we envisage this could be implemented and maintained centrally by forest agencies—ideally in a cloud-based platform to allow open access and wide usage. By running this centrally, it could lead to a large user community, many of whom may not be trained in remote sensing but tasked with monitoring forest disturbance at the landscape scale. Users could then be notified of changes in stands of interest through targeted alerts provided by the system.

Once a disturbance for an area is flagged, targeted data acquisition may be required. In remote areas, high–spatial-resolution satellite data may be sufficient to assess the disturbance and identify potential next steps. In more accessible areas, RPAS acquisition or field sampling could be performed. Either way, the framework would need to trigger some additional imagery capture or field work programme to allow additional investigation into the disturbance and its implications on the forest resource. This is also where private–public partnerships and links to forest consulting companies are needed to allow additional resources and expertise to be utilized to both obtain this more detailed information, as well as aid in its interpretation. Detailed and timely knowledge of disturbance severity, location and type will help determine the necessity for management responses such as salvage harvest or planting. Likewise, this targeted data acquisition allows for the efficiency of management to be improved, due to a likely shift from systematic sampling towards sampling based on areas of interest (Queinnec *et al*., 2021). When implemented, we believe the proposed framework can improve the timeliness and level of detail associated with forest inventories. An enhancement to the information quality in this way can undoubtedly be beneficial to forest management, particularly given the challenges seen in the present and changes expected in future.

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Conflict of interest statement

None declared.

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Data availability

The data underlying this article will be shared on reasonable request to the corresponding author.

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