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Satellite-based time series land cover and change information to map forest area consistent with national and international reporting requirements

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Forests are dynamic ecosystems, subject to both natural and anthropogenic agents of change. Wildfire, harvesting and other human activities alter the tree-covered area present in forests. From national and international reporting perspectives, forests include areas currently treed, as well as those disturbed forest areas that are not currently treed but will be, given time for regeneration and the advancement of natural successional processes. As a consequence, forest area can be depicted at a particular point in time, informed by a retrospective temporal context. Using time series of Landsat imagery, annual land cover maps can be generated that are informed by knowledge of past disturbance history (such as wildfire and harvesting). In this research, we use over three decades of annual land cover data generated from Landsat time series to generate a spatially explicit estimate of the forest area of Canada in 2010. We demonstrate how land cover and disturbance information can be combined to map the area of 'forest', as defined by the Food and Agricultural Organization of the United Nations (FAO), within Canada's 650 Mha of forested ecozones. Following this approach, we estimated Canada's total forest area in 2010 to be 354.5 Mha. This estimate includes 324.5 Mha of current forest cover in 2010, plus an additional 33.2 Mha (or 9.4 per cent) of temporally informed forest area where tree cover had been temporarily lost due to fire or harvest, less 3.3 Mha that were removed to meet a definitional minimum size (0.5 ha) for contiguous forest area. Using Canada's National Forest Inventory (NFI) as an independent reference source, the spatial agreement between the two estimates of forest area was ~84 per cent overall. Aspatially, the total area of the Landsat-derived estimate of 2010 forest area and the NFI baseline estimates differed by only 3 per cent, with notable regional differences in the wetland-dominated Hudson Plains Ecozone. Satellite-derived time series land cover and change information enable spatially explicit depictions of forest area (distinct from representations of forest cover) in a robust and transparent fashion, producing information of value to science, management and reporting information needs.

Introduction

Land system change is a major global concern (Steffen *et al.*, 2015). Land conversion to human uses is one of the driving forces behind biodiversity loss and human-induced climate change. Forest conversion to non-forest is a particular concern. The combination of human pressures and climate change impacts are driving accelerated forest changes worldwide. Forest concepts and definitions affect our interpretation and understanding of forest changes (Chazdon *et al.*, 2016). Distinguishing forest area losses (i.e. conversion to non-forest land uses or deforestation) from tree cover losses, which may be temporary (i.e. natural disturbances, sustainable forestry) or which may eventually lead to forest area loss (i.e. unsustainable logging, altered successional pathways), is critically important for two reasons. Firstly, the impacts of permanent loss in forest area on biodiversity, ecosystem functioning and resource use opportunities are fundamentally different than the impacts of a temporary loss of forest cover. Secondly, different policy and management responses are needed to achieve sustainability in the face of forest area versus forest cover losses.

A century ago, concerns about forest degradation and loss led to the establishment of the first national forest inventory (NFI) programs. Most countries now maintain NFI programs (Vidal *et al.*, 2016). At first, these programs existed to quantify and track changes in forest area and wood supply. Now, they have been expanded to track a host of other attributes to support sustainable forest management (Kangas and Maltamo, 2006). Forest inventory and monitoring activities are critical to management planning, assessing the sustainability of forestry practices and understanding natural drivers of forest change (MacDicken *et al.*, 2015).

Forest area is a key variable of interest for national and international reporting obligations. Net forest area loss can be indicative of unsustainable development (Kurz, 2010). Despite the importance of forest area as a sustainability indicator, it is often subject to variability in reporting, with tree cover and forest area erroneously conflated. The importance of this distinction between forest area and tree cover is recognized by the Food and Agriculture Organization of the United Nations (FAO). The FAO (2018) defines forest as 'Land spanning more than 0.5 hectares with trees higher than 5 meters and a canopy cover of more than 10 percent, or trees able to reach these thresholds in situ. It does not include land that is predominantly under agricultural or urban land use'. This definition provides minimum thresholds for land area size, tree height and canopy cover. The definition includes lands that do not currently satisfy the tree cover or height criteria, but are expected to. The intent is to include lands in all stages of natural forest succession or managed forest harvest rotations because these contribute to future wood supply and to the provision of environmental services, such as carbon uptake. Treed lands that are predominantly under agricultural or urban land use are explicitly excluded; although trees provide important services on agricultural and urban lands, these differ from the services they provide in forests.

The FAO's periodic Global Forest Resources Assessments (GFRA) are compiled using national forest statistics, most of which are produced by NFI programs (MacDicken, 2015). *In situ* survey data collection at permanent ground plots and design-based statistical inference have been the standard NFI approach from the outset, but NFI programs are now evolving to take advantage of new remote sensing technologies and meet growing demands for information about small areas, remote areas and full area mapping (Barrett *et al.*, 2016). NFI programs typically define 'forest' in a manner that is generally consistent with the FAO definition. Forest cover changes detected by remote sensing, however, can be significantly different from forest area changes reported by countries in national communications, in the GFRA and in other international reporting processes. Hansen *et al.* (2013) explained that this situation is unsurprising because the variables being assessed are different; remote sensing studies report changes in tree cover (land cover), whereas nations and the GFRA report changes in forest area (land use). Discrepancies are greatest where deforestation and afforestation are not the predominant causes of forest cover loss and gain, respectively. Nontechnical users of the information, however, can be easily misled. Precision bias—the cognitive bias caused by the natural human tendency to confuse accuracy and precision—causes people to instinctively trust spatially precise digital map products more than design-based statistical estimates. Currently, the former are available for forest cover, but only the latter are available for forest area. It would be useful to have detailed forest area maps that are consistent with the FAO definition so that these could be used in conjunction with design-based NFI data to provide more spatially precise forest area information products.

Canada is an ideal case study for the development and demonstration of wall-to-wall forest area mapping methods that are consistent with the FAO definition of forest because of the challenges (e.g. large area, multiple jurisdictions and range of disturbances) present in Canada and the global significance of Canada's forests. Forest-dominated ecozones occupy ~650 Mha in Canada (Wulder *et al.*, 2008). Forests are present over 347 Mha (Natural Resources Canada, 2018), mostly located in forest-dominated ecozones. Canada's forests represent 9 per cent of the world's forests (FAO, 2015). Some of the largest remaining tracts of contiguous forests (often described as intact forest landscapes) are located in Canada (Potapov *et al.*, 2017; Venier *et al.*, 2018). Most forests are on publicly owned lands where resource management is governed by provincial or territorial government legislation and regulations. Deforestation rates are low, and the dominant causes of forest cover loss nationally are natural (White *et al.*, 2017; Natural Resources Canada, 2018) with wildfire occurrence projected to increase in the future under changing climate conditions (Price *et al.*, 2013). The forest area is stable as most forest cover losses and gains in Canada are not related to changes in forest area.

In this research, we used satellite (Landsat)-derived land cover (Hermosilla *et al.*, 2018) and attributed forest change information (Hermosilla *et al.*, 2016) to generate a spatially explicit map product and estimate of forest area for the year 2010. We then investigated how these estimates vary from existing estimates and how that could impact reporting. The ultimate goal of this research is to demonstrate an approach for producing a satellite-based, wall-to-wall, spatially explicit forest area dataset towards operational use by Canada's NFI.

Materials and methods

Study area

Canada is nearly 1 billion ha in area, occupying much of northern North America. At the national level, Canada is generally represented by Arctic northern regions, an east to west band of forested ecosystems and agricultural/urban areas in the south. Forested ecozones (Figure 1A), as an assemblage of largely trees, wetlands and lakes, make up approximately 65 per cent of Canada's land area (Wulder *et al.*, 2008). Within the forested ecozones, there are differences in the species and structural expectations by both latitude and longitude. Northern extents of the forested ecozones, for instance, have lower productivity, smaller trees and more open canopies. Southern forests are the converse, higher productivity, larger trees, more species and more structural complexity. From west to east, moisture regimes also vary with the west being more dry and subject to wildfire than the east (Brandt *et al.*, 2013). Over 90 per cent of Canada's forests are publicly owned (Natural Resources Canada, 2018). Forest harvesting is concentrated close to transportation networks in more highly productive, southern forests. Most harvesting occurs on public (Crown) lands under the jurisdiction and stewardship of provincial and territorial governments. Wildfires can occur anywhere in Canada's forests,

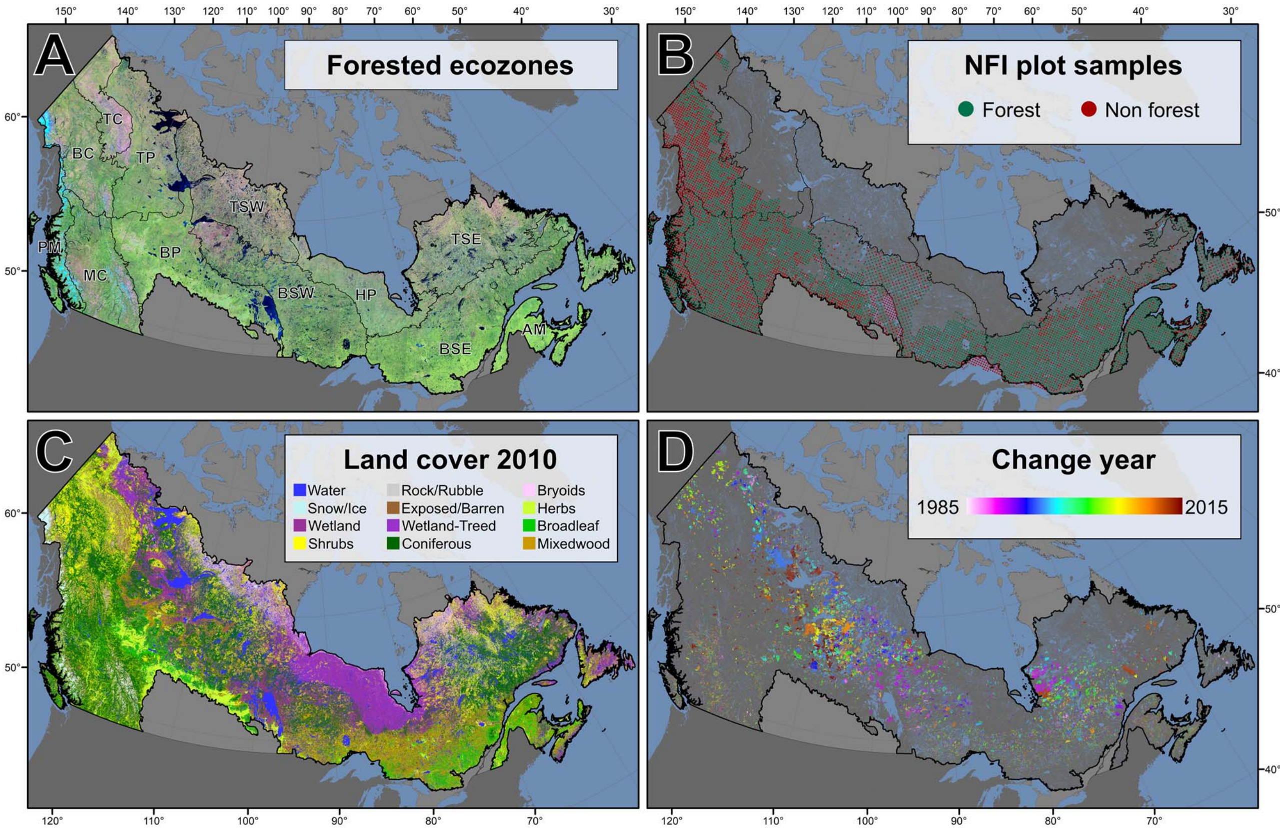

Figure 1 Study area and data: (A) false-colour Landsat image composite of Canada 2010 overlaid with Canada's forested ecozones: Atlantic Maritime (AM), Boreal Cordillera (BC), Boreal Plains (BP), Boreal Shield East (BSE), Boreal Shield West (BSW), Hudson Plains (HP), Montane Cordillera (MC), Pacific Maritime (PM), Taiga Cordillera (TC), Taiga Plains (TP), Taiga Shield East (TSE) and Taiga Shield West (TSW). (B) Location of the National Forest Inventory (NFI) photo plot samples. (C) 2010 land cover map produced with the Virtual Land Cover Engine (VLCE) framework (Hermosilla *et al*., 2018). (D) Annual stand-replacing forest disturbances for 1985–2015 produced using the Composite2Change (C2C) approach (Hermosilla *et al*., 2016). This figure appears in colour in the online version of *Forestry*.

but the most fire-prone forest ecosystems are in the Boreal, Taiga and Cordillera ecozones. The area affected by wildfire varies between years, but on average a larger area is affected by wildfire compared with harvesting (White *et al*., 2017; CCFM, 2019; Natural Resources Canada, 2019). Insects and disease are also present, often impacting greater areas than wildfire or harvesting; although, these impacts often do not lead to mortality. Because of the large extent of Canada's forests coupled with the diversity and widespread nature of disturbances, forest monitoring is critical for understanding and reporting on the status of this important environmental and economic resource. In this research, we consider the entire 650 Mha of Canada's forested ecozones.

Data

National Forest Inventory (NFI) data

Similar to other nations, Canada's reporting on forest area to the FAO definition is based on NFI data. Photo-interpreted attributes from a remote sensing survey constitute the core data in Canada's NFI because the country is too large and many of its forests are too remote to monitor cost-effectively using traditional, design-based field survey techniques (Gillis *et al*., 2005). The remote sensing survey consists of square (2 × 2 km; 400 ha) sampling units (photo plots) located on a systematic, national sampling grid (i.e. every 20 km). Permanent field survey units (ground plots) are maintained in a subset of the photo plots, but data collected at these ground plots are currently not used in forest area estimation. NFI data are collected on a 10-year remeasurement cycle and are not subject to a formal accuracy assessment.

Four layers of information are collected for each photo plot: land cover, land use, ownership and protection status. Two of these—land cover and land use—are used to assess forest area. Stereo photography flown at scales ranging from 1:10 000 to 1:20 000 are the preferred imagery data for NFI land cover assessment due to their high degree of spatial detail and the opportunity to interpret and measure land cover and forest attributes stereoscopically (Gillis and Leckie, 1995). However, as a result of logistical considerations, high-resolution (50 cm or better) optical satellite imagery is often used instead (Falkowski *et al*., 2009). Land use data are collected from official sources and harmonized to the NFI land use classification system (Canadian National Forest Inventory Committee, 2008).

Landsat-derived land cover and forest change information

Land cover and forest change information were derived from Landsat time series. Forest change information were derived from the datasets produced using the Composite2Change (C2C) approach (Hermosilla *et al*., 2016). The C2C approach involves creating annual best available pixel (BAP) image composites representing growing season conditions by selecting optimal pixels from all available archived Landsat data (White *et al*., 2014). The BAP composites are refined and further analysed using temporal trend analysis (Hermosilla *et al*., 2015a), resulting in annual time series of gap-free, surface reflectance composites and the detection, delineation and characterization of annual forest changes (Figure 1). Detected forest changes were attributed to a change type (i.e. fire, harvest, road and non-stand-replacing disturbance) following a random forest classification model based on their spectral, geometrical and temporal characteristics (Hermosilla *et al*., 2015b). Forest change products were evaluated using an independent set of reference data, resulting in 89 per cent overall accuracy for change detection and 92 per cent overall accuracy for change type attribution (Hermosilla *et al*., 2016). Landsat-derived forest change information has been made openly available online and can be freely downloaded from https://opendata.nfis.org/mapserver/nfis-change_eng.html.

Treed areas were derived from the annual land cover maps of Canada produced using the Virtual Land Cover Engine (VLCE) framework introduced in Hermosilla *et al*. (2018). The VLCE framework encompasses the initial production of a preliminary annual land cover classification using a random forest classifier based on spectral characteristics derived from the Landsat composites and topographic data. This results in an initial stack of annual land cover information. Following this preliminary classification, a hidden Markov model was applied to the annual stack to incorporate forest change information, year-to-year vegetation succession expectations and expert-based class transition likelihoods (Abercrombie and Friedl, 2016) to produce temporally consistent maps with ecologically coherent land cover class transitions (Gómez *et al*., 2016; Wulder *et al*., 2018a). These land cover map products (Figure 1C) have 12 land cover classes, including non-vegetated (water, snow/ice, rock/rubble, exposed/barren land), vegetated non-treed (bryoids, herbs, wetland, shrubs) and vegetated treed (wetland-treed, coniferous, broadleaf, mixedwood) after Wulder *et al*. (2008). Land cover products were assessed using an independent set of validation samples resulting in an overall accuracy of 82.5 per cent in the discrimination between treed vegetation, vegetated non-treed and non-vegetated (Hermosilla *et al*., 2018).

Methods

NFI forest area: reference data for assessment

Classification of surveyed lands as forest or non-forest is conducted using photo-interpreted land cover attributes together with land use information in a sequence of logical steps:

1. All vegetated, treed land having ≥5 m site height is classified as forest.
2. All vegetated, treed land having <5 m site height and site index ≥3 is classified as forest.
3. All vegetated, treed land having <5 m site height and site index <3 where there is evidence of a previous stand and regeneration is classified as forest.
4. All vegetated, non-treed upland where land use is forestry is classified as forest.
5. All vegetated, non-treed upland where land use is not forestry but there is evidence of a previous stand and regeneration is classified as forest.
6. All non-vegetated land where land use is forestry and land cover class is conducive to growing trees (exposed soil, burned areas, landings, logging roads) is classified as forest.
7. All land where land use is agriculture or settlement (except protection forest) is classified as non-forest, even if it was classified as forest by one of the steps above.
8. All else is classified as non-forest.

In the NFI land cover classification scheme level 1, surveyed lands are classified as vegetated or non-vegetated; in level 2, vegetated lands are classified as treed or non-treed; and in level 3, vegetated lands are classified as upland, wetland or alpine (Natural Resources Canada, 2008). In the NFI land use classification scheme, surveyed lands are classified as industrial, forestry, agriculture, conservation, infrastructure, settlement, recreation, national defence or unknown (Canadian National Forest Inventory Committee, 2008). Stand attributes are derived from ocular estimates made by a trained photointerpreter using digital stereo softcopy photogrammetry. Photointerpreters use ground checks and ancillary data in the area to be interpreted to ensure familiarity with forest conditions. Stand height is defined by the height of the leading species in the dominant tree layer of the stand. The leading species is defined as the species with the greatest percentage of stems in the stand. Site index for the stand is subsequently modelled as a function of stand age, height and leading species, with unique site index equations used for different tree species and regions of the country (Natural Resources Canada, 2004, 2008).

To support the comparison process, NFI land cover and forest/non-forest classification information was extracted using 30 m spaced samples aligned with the centres of a grid of Landsat pixels. To avoid edge effects related to polygon boundaries, samples are buffered to be at least 45 m away from polygon boundaries (Figure 2). As a result, for this comparison each forest inventory polygon in the NFI is represented by a number of points on a 30 m grid that coincide with the centre coordinates of a Landsat pixel. These within-NFI polygon values are hereafter referred to as plot samples.

To meet the NFI forest area definition, forest inventory polygons are combined with land use and ownership vector layers, often resulting in the creation of smaller polygons. Here, the previous NFI measurement cycle (circa 2000) solely based on interpreted stereo photography (8907 photo plots; Figure 1B). From the full sample of photo plots, 880 063 polygons from 398 746 interpreted stands are represented by 14 441 733 plot samples (which excluded those found over agricultural regions[1]). The full sample set was used to assess the correspondence between the NFI baseline land cover labels and Landsat-derived forest area

1 https://open.canada.ca/data/en/dataset/58ca7629-4f6d-465a-88eb-ad7fd3a847e3

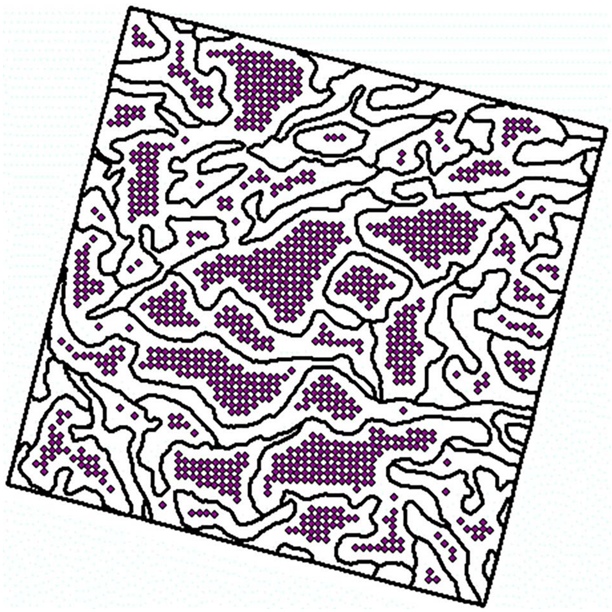

Figure 2 Example of the Landsat-aligned 30 m sampling done within stands (or smaller polygons) of interpreted photo plots used to asses agreement between Canada's NFI and our new Landsat-derived forest area map. To avoid potential noisy information at boundaries, samples are 45 m away from polygon boundaries.This figure appears in colour in the online version of *Forestry*.

product categories. Given the temporal mismatch between NFI data (collected over a multi-year period) with the singular year satellite-derived information, spatial agreement was assessed excluding any points with evidence of change (Hermosilla *et al.*, 2016) within Canada's forest-dominated ecozones, resulting in 8314 photo plots represented by 12 742 869 plot samples. Forest and non-forest agreement between these plot samples and the 2010 Landsat-derived forest area product was used to inform a spatially explicit assessment of the output forest area.

Definition of forest area from Landsat-derived land cover and forest change information

The production of the Landsat-based forest area map for a given year is based on combining the current forest cover of that year (e.g. 2010) with an additional temporally informed forest extent that is obtained by looking at past disturbances and checking whether those pixels were forested before the disturbance event (Figure 3). Pixels that were forested before the disturbance event are expected to recover and be forested (by definition) once again.

Our objective was to derive a forest/non-forest classification dataset for Canada's forested ecozones for the year 2010 that is consistent with the FAO definition of forest (FAO, 2018). The FAO defines forest as those areas other than under agricultural or urban land use with a minimum size of 0.5 ha ('land spanning more than 0.5 hectares') that are covered by treed vegetation ('with trees higher than 5 meters and a canopy cover of more than 10 percent') and also areas that are expected to be covered by treed vegetation with those characteristics in the future ('able to reach these thresholds in situ'). Following the FAO definition of forest, we specified three conditions over the Landsat-derived land cover, after masking out agricultural and urban land use areas: (1) current forest cover condition, (2) temporally informed forest cover condition and (3) minimum size condition. Areas dominated by agricultural activities were identified and excluded from the analysis using the agricultural mask provided by Agriculture and Agri-Food Canada. The current forest cover condition identified the extent of forest cover in 2010 by selecting those pixels classified as treed classes (i.e. wetland-treed, coniferous, broadleaf and mixedwood) in the 2010 VLCE land cover map of Canada (Hermosilla *et al.*, 2018). The temporally informed forest condition identifies those pixels that were not classified as treed vegetation in 2010, but for which temporal context (1984–2009) suggested that those pixels are temporarily non-stocked forest. Temporal context was established using C2C forest change information (Hermosilla *et al*., 2016) to identify recently disturbed areas (i.e. harvest or wildfire since 1984) and pre-disturbance land cover information from a stack of annual VLCE land cover classifications. Disturbed areas may be temporarily non-stocked or in an early successional condition that is not classified as treed by VLCE in 2010. Pre-disturbance condition of recently disturbed pixels was analysed by assessing the land cover 2 years prior to the disturbance (as per White *et al*., 2017). Those pixels disturbed by fire or harvest events that were treed 2 years immediately before the disturbance are presumed to be temporarily non-stocked or early successional forest, which, given adequate time, will become treed again. Finally, the minimum size condition filters out areas smaller than the minimum size of 0.5 ha defined by (FAO, 2018), so that these are not classified as forest.

Graphical examples of the application of the current forest cover condition and the temporally informed forest cover condition are shown in Figure 4, where several land cover time series for given pixels are depicted. The year where the forest cover is assessed is represented by the focus year. Those pixels presenting tree cover in the focus year (Figure 4A and C) fulfil the current forest cover condition and are classified as forest. Figure 4B shows an example of a pixel that fulfils the temporally informed forest condition. The land cover for this pixel is not treed in the focus year, but the time series analysis indicates that a fire occurred in the pixel, and it had tree cover before the disturbance, so this pixel is expected to become treed again in the future and is therefore classified as forest. In contrast, Figure 4F exemplifies a case of deforestation, where a pixel that was covered by treed vegetation is disturbed by the construction of a road. Due to the nature of the disturbance, this pixel is not expected to become treed again in the future and hence does not fulfil the temporally informed forest condition. Disturbance-type information is used to distinguish pixels in the circumstance illustrated in Figure 4B (temporally informed forest condition) from the circumstance illustrated in Figure 4F (non-forest). Figure 4E displays an example of a pixel with persistent shrub cover and no evidence of disturbance or tree cover throughout the time series. Such pixels are classified as non-forest. Figure 4D shows a pixel that is non-treed forest in the focus year, but does not satisfy the temporally informed forest condition because the disturbance type is unknown. This particular case would be classified as forest by the current forest condition the following year if the dataset was being updated annually.

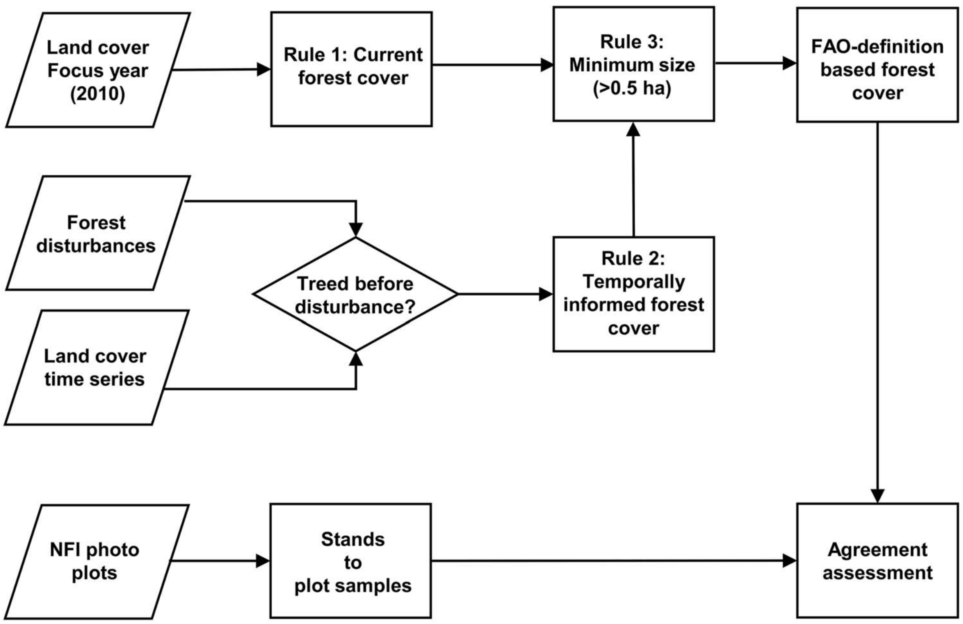

Figure 3 Flowchart of the methodological approach used to define forest area in 2010 from Landsat-derived land cover and forest change information.

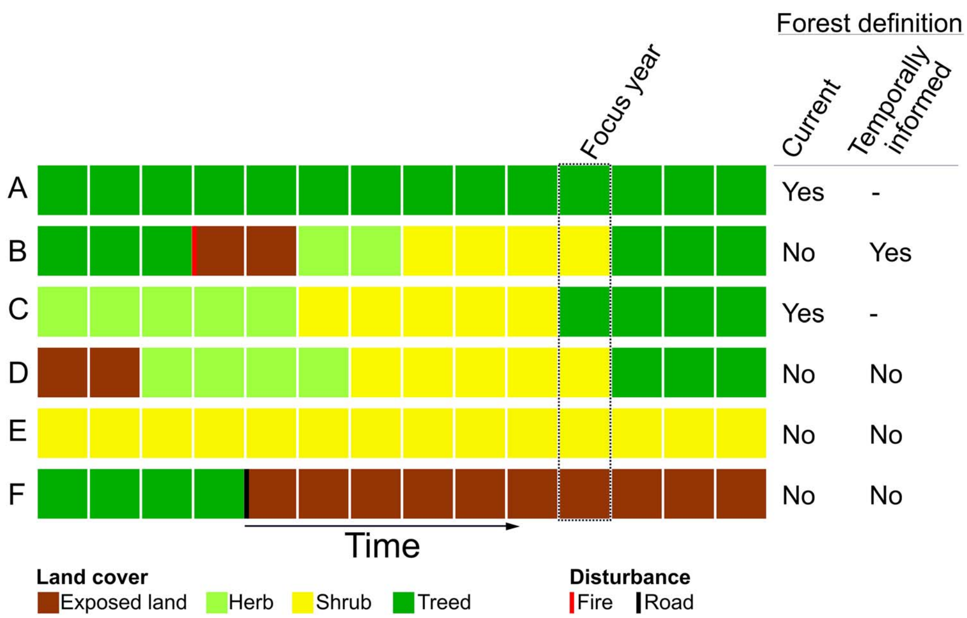

Figure 4 Examples of land cover time series for given pixels and their identification as forest by the current forest cover condition (single year) and the temporally informed forest condition (multiple years, knowledge of historic land cover). This figure appears in colour in the online version of *Forestry*.

Assessment of forest area product

The Landsat-derived spatially explicit representation of forest area for 2010 was assessed against the NFI baseline data to determine the degree to which the two estimates of forest area corresponded—both spatially and aspatially. An aspatial assessment compared the total forest area reported nationally and by ecozone. A spatial assessment of the Landsat-derived forest area for 2010 was undertaken using the NFI forest sample plots described in NFI forest area: reference data for assessment section. Further, to offer insights regarding the comparison between forest area values derived from polygon-based NFI and the pixel-based satellite-derived products, we generated a majority value for reconciliation and comparison. This allows for a one-to-one comparison to complement the detail provided by the one-to-many comparison.

To analyse the impact of time on the area classified as forest, we applied the approach annually from 2010 to 2015 to the land cover time series, using the C2C forest change information

Table 1 Contribution of each definition condition to the forest area for the year 2010.

Condition	Forest area (ha)
2010 forest cover	324 549 619
Temporally informed forest cover	33 231 237
Minimum size (<0.5 ha)	-3 284 647
Total	354 496 209

to provide temporal context. The resulting annual Landsat time series-based forest areas were then analysed based on the condition fulfilled (i.e. current forest condition or temporally informed condition), and changes in the annual forest area were assessed using the Theil–Sen nonparametric regression (Sen, 1968). The Theil–Sen method computes all pairwise slopes of forest area through time, returning the median slope. Theil–Sen slopes are commonly used in time series analyses since their slopes are less sensitive to outliers than traditional linear regression. A Mann–Kendall test was used to estimate slope significance (Bevan and Kendall, 1971).

Results

The Landsat time series-based forest area in Canada's forest ecozones for the year 2010 is shown in Figure 5. The forest area in 2010 includes the currently treed areas (dark green) plus the areas identified as temporarily non-treed forest (light green), minus those areas that were smaller than 0.5 ha (not shown). The contribution to the forest area by each condition is shown in Table 1. The area satisfying the current forest cover condition in 2010 was 324.5 Mha. The area satisfying the temporally informed forest cover condition was 33.2 Mha. The application of the minimum size condition removed 3.3 Mha of forest area, giving a total forest area of 354.5 Mha for Canada's forest-dominated ecozones. Spatial patterns in this dataset show where forests were being harvested (Figure 5A) and disturbed by wildfire (Figure 5B). Approximately 9.4 per cent of the forest area in 2010 is area that is currently non-treed, but was treed previously and is poised to be treed in the future.

The spatially explicit comparison of forest/non-forest classification between NFI plot samples and Landsat time series-based approach for the year 2010 (Table 2) indicates an agreement of 84 per cent. Using NFI as reference for comparative purposes, the Landsat time series-based approach identifies more forest area (forest class commission = 17.8 per cent, non-forest class omission = 20.7 per cent) compared with the forest area identified in NFI plot samples. The agreement between NFI and Landsat time series approach in each ecozone is shown in Table 3. Highest agreement was found in the Atlantic Maritime, Boreal Shield East and Boreal Shield West ecozones (≥90 per cent), whereas the lowest agreement was found in the Hudson Plains (65.5 per cent) and Taiga Plains (64.7 per cent) ecozones.

The comparison of forest area in Table 3 indicates that once forest patches of less than 0.5 ha (3.3 Mha) are excluded, the Landsat time series approach classifies 11 Mha more forest area than the NFI baseline estimates. Agreement for the study area overall is strong, as indicated by the Landsat-derived NFI ratio of 1.03. This strong overall agreement is partly caused by compensating discrepancies between the two estimates. For example, the Landsat time series approach classifies less area as forest in the Taiga Cordillera relative to the NFI baseline (19 per cent less) and classifies more area as forest in the Boreal Cordillera (18 per cent more). The greatest discrepancy is in the Hudson Plains, where Landsat time series approach classified 89 per cent more area as forest. The Hudson Plains is a wetland-dominated ecozone; following the NFI, wetland-treed is a treed land cover class. The marked discrepancy between the area classified as forest by the Landsat time series approach compared with the NFI baseline arises from issues related to land cover classification in wetland-dominated ecosystems and the paucity of forest inventory data in this region. As discussed in Wulder *et al*. (2018a, b), wetlands are a land condition and not a pure land cover category. Data issues such as image date can influence moisture conditions and the presence (or not) of standing water, which is known to have a notable impact on spectral values (Gallant, 2015). Besides within-year considerations, between-year run-off and precipitation amounts also influence the land cover in the Boreal Plains Ecozone (a region with seasonally and/or annually variable occurring wetlands). These issues affect both the VLCE and the NFI baseline because it was not possible to collect stereo photography or high-resolution satellite imagery uniformly at the national level. For instance, in the Hudson Plains for the NFI, baseline estimates were based on a Landsat-based land cover classification product (Wulder *et al*., 2008) with imputed site height and site index.

We further explored whether the correspondence between the NFI baseline land cover labels and the areas identified using the Landsat time series approach satisfies the current forest condition or the temporally informed condition using the full sample set (Table 4). There is correspondence of current forest condition in 73.93 per cent of plot samples. However, 16.50 per cent of plot samples satisfy the current forest cover condition but are classified as non-treed land cover in NFI baseline. The discrepancy in these plot samples may have been caused by differences in land cover classification methodology (VLCE land cover classification versus NFI photo-interpretation) or by cover changes between NFI baseline (2000–2006) and our 2010 focus year. More than half (52 per cent) of the plots defined as forest by the temporally informed condition were labelled as exposed land, herb or shrub in NFI baseline.

There is a diversity of land cover classes possible within an NFI photo plot polygon, yet stand level mapping only allows for a single category. We addressed this issue by pooling (aggregating) the land cover pixels within a given NFI polygon by assigning the majority pixel class (forest, non-forest) for comparison. While there are a number of ways to represent pixels within polygons (see Wulder *et al*., 2006), majority offers a simple and transparent means for comparison. We find an agreement of 85.6 per cent when assessment was conducted at the polygon level (one-to-one) versus the 84 per cent reported in Table 2 summarizing the many-to-one assessment.

Figure 6 shows the Landsat time series-based forest area annually from 2010 to 2015 and the condition fulfilled (i.e. current forest condition or temporally informed condition). Overall, there is no significant slope (Mann–Kendall test), but

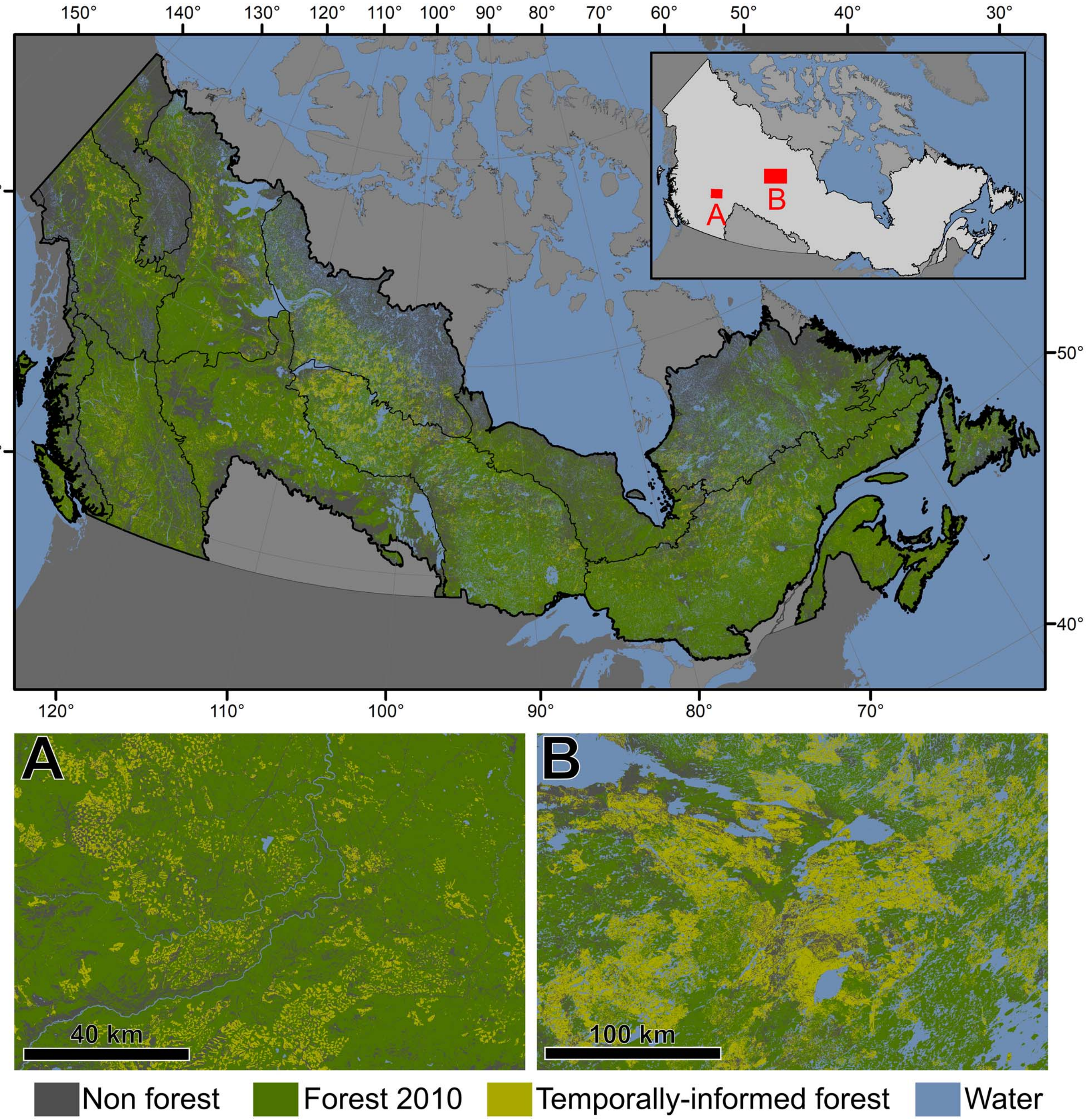

Figure 5 Landsat time series-based forest area for the year 2010 categorized by definition condition: current forest area and temporally informed area. Regionally detailed insets show (A) harvest and (B) wildfire disturbance dominated areas. This figure appears in colour in the online version of *Forestry*.

the current forest condition (area that is treed in each year) has a small but significant increase (Thiel Sen slope = 0.1 Mha year^{-1}). The positive slope in the Landsat time series yearly forest area overall can be understood by re-examining Figure 5. If we move the focus year forward in time by 1 year, then case Figure 4D satisfies the current forest condition, and we have an increase in area classified as forest. As the time series grows longer, fewer such additions to the area classified as forest occur. Given a sufficiently long time series, we would expect to see no slope if the forest area is stable. An especially long time series is needed in high-latitude forests, where recovery after disturbance is slow (Bartels *et al*., 2016; White *et al*., 2017).

Discussion

In this research, we used satellite-derived land cover and attributed forest change to produce a spatially explicit map of forest area for Canada. Combining land cover and time series-based attributed change information enables distinguishing

Table 2 Agreement between NFI plot samples and Landsat time series-based forest area for the year 2010.

		Landsat-derived			
		Non-forest	Forest	Total	Omission
NFI	Non-forest	4 862 172	1 266 112	6 128 284	20.70%
	Forest	772 306	5 842 279	6 614 585	11.7%
	Total	5 634 478	7 108 391		
	Commission	13.7%	17.8%		
				Agreement	84.0%

Commission and omission computed using NFI plot samples as reference.

Table 3 Ecozone-level agreement between NFI plot samples and Landsat time series-based forest area for the year 2010. Forest area values derived from Landsat time series approach and NFI baseline estimates are compared. Note that NFI baseline estimates combine Boreal Shield East and West, and the Taiga Shield East and West.

Ecozones	Agreement	Landsat time series-based forest area (ha)	NFI baseline forest area estimates (ha)	Area ratio Landsat : NFI
Atlantic Maritime	91.1%	15 834 141	16 295 668	0.97
Boreal Cordillera	74.9%	22 542 829	19 116 462	1.18
Boreal Plains	83.6%	42 383 647	38 454 654	1.10
Boreal Shield East	90.0%	77 576 440	131 274 726	1.00
Boreal Shield West	91.6%	54 036 365		
Hudson Plains	65.5%	18 591 531	9 857 724	1.89
Montane Cordillera	86.5%	31 066 165	31 128 471	1.00
Pacific Maritime	88.2%	11 366 866	10 744 095	1.06
Taiga Cordillera	79.1%	5 241 016	6 442 884	0.81
Taiga Plains	64.7%	31 102 385	33 601 171	0.93
Taiga Shield East	85.9%	27 447 142	46 292 885	0.97
Taiga Shield West	86.8%	17 307 682		
Total	84.0%	354 496 209	343 208 740	1.03

Table 4 Correspondence between NFI baseline land cover labels and Landsat time series-based forest definition condition applied for the year 2010, by land cover class.

	Landsat time series-based forest area (%)	
NFI class	Current forest cover	Temporally informed forest cover
Bryoid	0.71	0.09
Exposed land	0.22	0.46
Herb	2.25	1.54
Missing info	0.65	0.04
Rock	2.10	0.02
Shrub	10.29	3.01
Snow ice	0.08	0.00
Treed	73.93	4.40
Water	0.19	0.01
Total	90.43	9.57

between changes in land cover that imply a change in land use. As presented in Figure 6, when considered in aggregate, forest area in Canada is relatively stable over time as having no, or only slight, differences on an annual basis. Forests in Canada are dynamic, however, with notable areas of forest cover gain and loss. Given the large overall extent of Canada's forests, the ongoing changes are largely offset, whereby historic changes move into treed classes as new disturbance results in a temporary allocation to a non-treed condition (see Figure 8 in Hermosilla *et al.*, 2018). Most forest cover losses in Canada are caused by natural disturbance or timber harvesting on publicly owned lands governed by provincial government legislation and regulations. Most timber harvesting in Canada occurs on lands that are under an independently verified forest management certification scheme (Natural Resources Canada, 2018), and so it can be assumed, for forest area mapping purposes, that harvested areas will regrow (White *et al.*, 2017). Regeneration success following harvesting and natural disturbances should be monitored, of course, but forest/non-forest classification is not the best tool for that task (White *et al.*, 2018). However, by differentiating areas satisfying the current forest cover condition in 2010 from those satisfying the temporally informed forest condition, the Landsat time series approach reported here provides information that could be useful for tracking the area of non-stocked forest over time, especially over the large area under analysis.

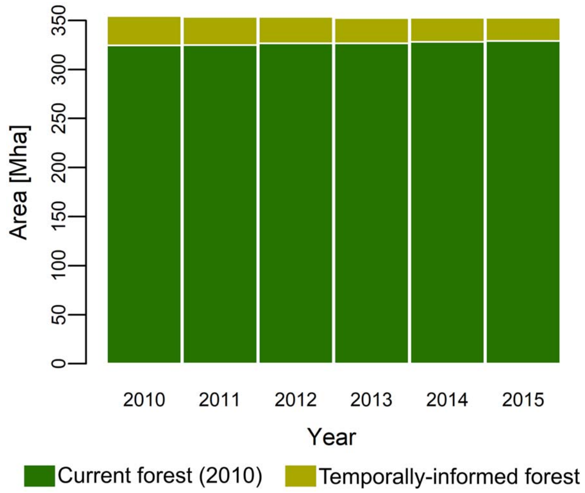

Figure 6 Annual Landsat time series-based forest area from 2010 to 2015. Areas categorized by definition condition contribution: current forest condition (green) and temporally informed condition (olive). This figure appears in colour in the online version of *Forestry*.

Forest/non-forest classification over time should account for deforestation (conversion of forest to non-forest land use) or be informed by independent deforestation monitoring data. The approach presented herein accounts for deforestation (e.g. Figure 4F), but the degree to which it does so depends entirely on the accuracy of disturbance type attribution and on disturbance mapping data completeness. Deforestation rates in Canada are low, with ∼37 000 ha deforested per year currently, or 0.01 per cent of NFI reported forested area (Natural Resources Canada, 2018). Canada uses a special-purpose, survey-based monitoring programme to estimate the annual area of deforestation (Dyk *et al*., 2015). This approach is used to produce estimates for national reporting, but it does not produce wall-to-wall mapping data that could be used as an input to the Landsat-based time series approach to forest/non-forest classification reported here. Changes in forest area (e.g. slope in Figure 6) may be indicative of net forest area loss or gain, but they should not be interpreted as estimates of net forest area loss or gain, as source information may not be sufficiently precise. New forest areas emerging over time could be investigated to determine if these are indicative of slow forest recovery, as discussed previously, or actual forest area gain. Afforestation is not monitored nationally in Canada. The most recent data suggest that afforestation rates are extremely low relative to the overall forest area (White and Kurz, 2005). The forest/non-forest classification approach presented here could potentially identify afforested sites, but methodological changes would be required, such as an update of the agricultural land mask to reflect the change in land use.

The FAO (2018) definition of forest requires treed areas to span at least 0.5 hectares. Applying this rule resulted in the removal of all treed patches smaller than 0.5 ha, which subtracted 3.3 Mha from the Landsat time series-based forest area for the 2010 focus year. Therefore, the minimum size condition rule implemented herein has a conservative effect on the classification of forest area. Alternatively, this condition ('land spanning more than 0.5 hectares') could be implemented using a minimum mapping unit (MMU), which indicates the size of the smallest element that is represented in the resulting map. The implementation of an MMU can decrease forest area by removing small treed patches, but it could also be expected in forest-dominated environments to increase forest area by relabelling small non-forest gaps within forest areas as forest.

As demonstrated herein, the mapping of forest area is complicated by the categorical, spatial and temporal elements under consideration. Differing definitions of forest area as well as data processing and analysis decisions have been shown to result in different mapped outcomes (Comber *et al*., 2010). A similar situation has been shown regarding the follow-on impacts of different forest definitions on determining reference levels for deforestation and related capacity to monitor subsequent changes (Romijn *et al*., 2013). Knowing that this capacity for variability in outcomes exists, transparency in reporting definitions applied, rules implemented and processing decisions made is critical.

Over time, international reporting objectives have become increasingly detailed, going beyond forest area to understanding additional qualities and context. Forest area remains important, but distinguishing between natural and plantation forests is an example of evolving interests. Previously, the FAO's Global Forest Resources Assessment (GFRA) has been criticized because the FAO definition of forest fails to distinguish natural forests from tree plantations. The declining rate of net forest loss reported in the 2015 GFRA (FAO, 2015; Keenan *et al*., 2015) was presented as a positive development at the 2015 World Forestry Congress, but critics highlighted that the data failed to report the issue of natural forest loss. Chazdon *et al*. (2016) argued for a richer concept of a forest than that offered by the FAO definition. One way to achieve this, and supported by remotely sensed spatial data on forests, is by taking multiple attributes into consideration, not just forest area. International sustainable forest management (SFM) processes, including the Montreal Process, Forest Europe and the International Tropical Timber Organization, have been promoting this approach by encouraging the use of criteria and indicators (C&I) that consider all three pillars of sustainability: ecological, economic and social. Progress toward global Sustainable Development Goals is tracked by monitoring forest area as a percentage of total land area (indicator 15.1.1), forest area net change (15.2.1.a), above-ground biomass stock in forests (15.2.1.b), proportion of forest area within legally established protected areas (15.2.1.c), proportion of forest area with a long-term management forest management plan (15.2.1.d) and forest area under an independently verified forest management certification scheme (15.2.1.e). The 2020 GFRA will also include data on area of naturally regenerated forest and planted forest, distinguishing plantations from other planted forests (FAO, 2018). Spatially explicit data on forest area that consider current forest cover as well as recent disturbance history with attribution, and regeneration expectations, could be used to support more detailed analysis of forest change and for identifying challenges to forest sustainability.

Given commonality of international forest area reporting requirements, it is possible that similar processes to those described herein can be adopted elsewhere. Considerations to adoption include availability of imagery, computational capacity and supplemental datasets (e.g. NFI, land cover). While the first Landsat satellite was launched in 1972, the data were not collected uniformly over space and time, with variability in not only the data density and distribution but also the nature of the data collected (Wulder *et al*., 2019). Importantly, with Landsat-4 (launched in 1982) and Landsat-5 (1984), the spatial resolution was improved to 30 m over a more broad suite of spectral band passes. Increased capacity for on-board recording of data combined with a global network of receiving stations led to an improved global representation of Landsat data. Following the launch of Landsat-7 (1999), an increasingly systematic approach to data acquisition was implemented with the aims of both global and seasonal representation of imagery (Wulder *et al*., 2016). Availing upon developments in on-satellite data recording capacity and higher rates for data downlink, Landsat-8 (2013) is essentially 'always-on' with regard to continental terrestrial data collection opportunities (Roy *et al*., 2014; Wulder *et al*., 2019). Key to use of Landsat data is the free and open access data policy allowing for reduced barriers to utilization and application of increasingly sophisticated algorithms (Zhu, 2017; Wulder *et al*., 2018a; Zhu *et al*., 2019). Similarly, Copernicus (the European Union's Earth Observation Programme) has a free and open data access policy, as well as provision of a number of tools (services) to accelerate and improve science and application outcomes (Drusch *et al*., 2012). Sentinel-2 is the Copernicus series of satellites with spatial and spectral characteristics compatible with Landsat. This compatibility enables the development of approaches whereby Landsat data can provide the 'history' to combine with measures from Sentinel-2 (Wulder *et al*., 2015). Sentinel-2 has finer spatial resolution than Landsat (and additional, vegetation informative, spectral channels) that are of value for improved depiction of forest change boundaries and features (e.g. roads) that may be subpixel and of limited detectability using Landsat data.

The free and open-access status of Landsat and Sentinel-2 data has fostered the development of many sophisticated cloud computing platforms (e.g. Gorelick *et al*., 2017). As an application example from an international forest monitoring point of view is SEPAL (System for Earth Observation Data Access, Processing and Analysis for Land Monitoring; https://github.com/openforis/sepal/wiki). Developed with international support and under the leadership of the UN Food and Agricultural Organization (Forestry Department), SEPAL provides monitoring capacity to the international community. Similar to the time series, cloud-based, computing implemented in this research, portability of the approach is encouraged by access to cloud computing tools and open-access satellite data. It is worth noting that many nations with smaller areas or internal capacity may not require a cloud computing solution to generate the relevant land cover and forest change data products. Nations with rich spatial archives of forest (or other) change information may be able to integrate these independent data products into a similar forest area monitoring application. Critical to any application, using remotely sensed land cover or from other sources, is knowledge (and appropriate incorporation) of the temporal representation of each data source (Comber and Wulder, 2019; Woodcock *et al*., 2019).

Conclusion

Monitoring data that provide no forest cover loss attribution or that fail to distinguish *forest area* loss/gain from *forest cover* loss/gain can lead to misunderstanding regarding the nature of the observed forest changes. This definitional mismatch can in turn lead to the development of ineffective or even counter-productive policy or management responses. The area of forest present in a given jurisdiction is a function of how forest is defined. The presence of natural and human disturbances as well as regionally unique successional processes and life cycles of trees results in situations when a location with forest land use may not have tree cover. The FAO defines forest to allow inclusion of temporarily non-treed areas. Annual land cover products are now available from time series satellite data representing multiple decades of land cover and dynamics. These data sources offer categorical and temporal insights to determine the context of land cover at a given point in time. The historical information provided by satellite-derived time series data makes it possible to identify forest areas that are temporarily occupied by non-treed land cover as result of their current (transitory) stand development stage following stand-replacing disturbances. Over Canada's forested ecozones, we found a strong agreement between forest area estimated in the NFI baseline and the independently generated Landsat time series forest area mapping approach using multi-decadal series of land cover classification data. These results demonstrate that compatible outcomes can be generated, providing remotely sensed derived information within inventory cycles and in a wall-to-wall fashion to augment sample-based NFI information content and enhance reporting capacity.

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Conflict of interest statement

None declared.

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