Classification of annual non-stand replacing boreal forest change in Canada using Landsat time series: A case study in northern Ontario

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Pre-print of published version

Reference:

Ahmed, O., M.A. Wulder, J.C. White, T. Hermosilla, N.C. Coops, and S.E. Franklin. (2017). Classification of annual non-stand replacing boreal forest change in Canada using Landsat time series: A case study in northern Ontario. Remote Sensing Letters. Vol. 81, No. 1, pp. 29-37.

DOI: http://dx.doi.org/10.1080/2150704X.2016.1233371

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Abstract
Standardized protocols for forest change detection and classification based on Landsat time series data are becoming more common for use in characterizing multi-decadal history or trends in forest dynamics. One such protocol, referred to as Composite-2-Change (C2C), is a highly automated process developed in Canada that is applicable across extensive forest regions and includes change detection and typing based on Best-Available-Pixel (BAP) image compositing, spectral trend analysis of breakpoints, object-based segmentation, and Random Forest (RF) classification. The aim of this Letter is to assess the classification accuracy of the Composite-2-Change (C2C) protocol in an eastern Canadian boreal forest environment in northern Ontario. Results demonstrated that the Landsat-derived change detection and attribution approach was approximately 90% accurate for stand-replacing forest change (fire, harvesting, roads), and approximately 75% for four non-stand replacing forest changes caused by spruce budworm and forest tent caterpillar defoliation, wetland and forest flooding caused by localized hydrological variations, and one class of multiple/other disturbances. The C2C protocol approach offers unique independent data layers for modeling that can be used to relate and inform on a range of substantive and subtle changes, which in turn can be labeled and tracked, offering otherwise unavailable information on forest dynamics over large areas.

1. Introduction

Natural and anthropogenic disturbance processes occur in Canada's forests resulting in land cover and forest change that must be carefully monitored for management and reporting purposes (Wulder et al 2009). Recently, the Composite-2-Change (C2C) standardized Landsat time series protocol to support such monitoring was developed (White et al. 2014, Hermosilla et al. 2015a, 2016). C2C is based on time series forest change detection and classification methods, and accuracies have been shown to be higher than results obtained through simpler methods (e.g., image differencing) and less temporally comprehensive data sets (Hall et al. 2007). For example, in a boreal region of Saskatchewan in western Canada, C2C annual land cover change detection of stand-replacing forest disturbances (e.g., fire, harvesting and road-building processes) was 90% accurate. Lower accuracies were obtained for detection of non-stand replacing forest disturbances associated with biotic (e.g., insect) and abiotic (e.g., flooding, desiccation) processes (Hermosilla et al. 2015b). At the highest level of stratification, i.e., change or no-change, an accuracy of approximately 89% was reported, with allocation to the correct year for over 89% of cases tested, and 98% were allocated within +/-1 year. Disturbances were allocated to type with an overall classification accuracy of over 92%. Additional testing was recommended: i) to document the use of the C2C Landsat time series protocol in other forest environments and ecoregions; and ii) to consider certain change features (e.g., roads) and non-stand replacing change in greater detail to increase the accuracy, comprehensiveness, and overall utility of the protocol.

Non-stand replacing forest disturbances are important to relate stress and possible alteration to the factors driving forest growth and vigour (Goodwin et al. 2008, Cohen et al. 2015). Mapping such ephemeral changes may provide additional insight into the nature of the underlying forest and land dynamics being captured in time series remotely sensed data (Cohen et al. 2002, Neigh et al. 2014). However, non-stand replacing changes are not often systematically mapped since they display a lower magnitude of change and typically are not associated with a change in land cover class (Hermosilla et al 2015b, Franklin et al 2015).

The current study was designed to assess annual forest change classification accuracy, with a focus on a selection of non-stand replacing changes, using the C2C Landsat time series protocol (Hermosilla et al. 2015a) in the Hearst Forest Management Area (HFMA: see Figure 1), a large, actively-managed area of the Canadian Boreal Mixedwood Region (Ecological Stratification Working Group 1996) in northern Ontario. The goal was to confirm the level of classification accuracy for change caused by forest fires, harvesting (e.g., clearcutting), road-building activities, and non-stand replacing change related to two major defoliating insect infestations and the local effects of variations in hydrological regimes. Patterns of defoliation and damage caused by less abundant forest insects, other non-stand replacing forest changes caused by forest disease, desiccation events (e.g., drought, winter burn), silvicultural practices, and areas experiencing multiple disturbances, also occur in this area (Hearst Forest Management Inc. 2011, Natural Resources Canada 2013). This Letter highlights the classification accuracy obtained with implementation of the C2C Landsat time series protocol in the HFMA for the period 1990-2010.

2. Study area and data

In the Hearst Forest Management Area, Black spruce (*Picea mariana Mill. B.S.P.*) is present with other conifer stands composed primarily of jack pine (*Pinus banksiana Lamb.*), white spruce (*Picea glauca Moench Voss*), balsam fir (*Abies balsamea L. Mill.*), and tamarack (*Larix laricina Du Roi K. Koch*). Deciduous species include aspen (*Populus tremuloides Michx.*) and white birch (*Betula papyrifera Marsh.*). Annual harvest up to approximately 7500 ha is primarily by clearcutting (Hearst Forest Management Inc. 2007). Wildfires of various intensities occur frequently with some forest fire suppression activity. Forest insect outbreaks are episodic in the area; for instance, extensive spruce budworm (*Choristoneura griseicoma Meyrick*) outbreaks in several areas of the HFMA occurred in 1996, 1997, 1998, 1999 and 2000 resulting in large areas of defoliation though limited stand mortality. Deciduous forest defoliation associated with outbreaks of forest tent caterpillar (*Malacosoma disstria Hubner*) was also widespread in several years and across a large part of the Hearst Forest.

The HFMA intersects six Landsat WRS-2 path/rows. The 1990-2010 Landsat time series consists of a total of 706 Landsat images acquired representing acquisition dates from 1988 to 2012. These data were atmospherically-corrected using the Landsat Ecosystem Disturbance Adaptive Processing System (LEDAPS) algorithm (Masek et al., 2006), masked for clouds/shadows (Zhu and Woodcock 2012), and processed into Best-Available-Pixel (BAP) composites (White et al 2014) based on pixel observations scored according to sensor acquisition with a target day of year (DOY) of 1 August (+/- 30 days), distance to clouds and cloud shadows, and atmospheric opacity. Data gaps (pixels with "no data" values) were filled with proxy values (Hermosilla et al 2015a, 2016). Reference data on forest composition, harvest, fire, insect outbreaks, and land cover included: i) GIS data compiled under local forest management plans (e.g., Hearst Forest Management Inc. 2011); ii) forest resource inventory data (Ontario Ministry of Natural Resources 2012); iii) forest fire maps (Amiro et al. 2001, Stocks et al. 2003); and iv) two recent satellite-based land cover classification products (Wulder et al. 2008, Franklin et al. 2015).

3. Methods

The major steps in the C2C Landsat time series protocol tested in this study were presented in detail by White et al (2014) and Hermosilla et al. (2015a,b, 2016) and are briefly highlighted here. The C2C time series annual change detection uses a breakpoint detection process based on spectral trend analysis and 'greatest-change' to identify change areas; in the HFMA, this step was determined to be over 92% accurate in identifying change for subsequent characterization and classification (see Franklin et al. 2015). Change characterization was accomplished by segmentation of change objects (minimum mapping size of 0.5 ha) based on date of occurrence and descriptive aspects of the change features such as duration (persistence) (Hermosilla et al. 2015a). For the present study, these change objects were then sampled for 1291 classification training and validation sites encompassing each of the forest change types of interest (e.g., roads/infrastructure, fire, harvest, insects, and flooding) based on the reference data sources, expert interpretation of digital colour infrared orthophotography of the HFMA acquired at 1:20000 scale in 2007, and limited field observations. These samples were well-distributed spatially and temporally (averaging approximately 2 km apart spatially across all years), thereby minimizing the effect of spatial autocorrelation, and the overall accuracy validated for the disturbances detected in the time series was considered reasonable for any given year based on the confirmation of year and disturbance type in the reference data (see also Hermosilla et al 2016). Change classification was based on 1090 of these 1291 training and validation sites, or change objects, in known stand-replacing forest change areas. A total of 561 change objects were classified in known non-stand replacing change areas.

The Random Forest machine learning algorithm (Breiman 2001) was employed with predictor variables selected from the available spectral- and trend-based metrics and geometrical descriptors following multicollinearity tests. Typically, the accuracy of change classification is difficult to assess due to a lack of consistent, fine spatial scale validation data which are temporally and thematically consistent over the entire Landsat observation period. Therefore, an out-of-bag (OOB) sample strategy was used with approximately 63% of the total (1291) samples employed to develop the RF decision rules. The remaining samples were used to validate each classifier run. When the sample size is large and well-distributed, this OOB approach has been shown to provide reasonable estimates of classifier error when compared to independent assessment error (Millard and Richardson 2015, Belgiu and Dragut 2016). The overall and individual classification accuracies are then presented in standard confusion matrices.

4. Results

The best RF classification iteration provided an overall classification accuracy of approximately 90% for three stand-replacing forest change classes and one general class of non-stand replacing forest change (Table 1). This level of overall classification accuracy is comparable to the C2C annual time series classification results reported in the boreal region of Saskatchewan by Hermosilla et al (2015b) and elsewhere using time series of Landsat imagery (e.g., Schroeder et al. 2011). Initially, the stand-replacing forest change classes displayed minor confusion with the non-stand replacing forest change class, which subsequently had the highest individual class omission errors (15%). As expected, the separation of this general non-stand replacing forest change into four discrete classes of change associated with different disturbance processes provided greater detail but lower overall classification accuracy (75.4% overall; see Table 2). Areas of spruce budworm defoliation were the least accurate (64% user's accuracy, 71% producer's accuracy). Such areas are known to present variable spectral responses based on severity of defoliation, original stand conditions, and other factors, including, for example, the date of image acquisition, local spectral context, and radiometric and geometrical characteristics (e.g., Franklin and Raske 1994). Temporal resolution of image data is known to strongly influence aspen defoliation mapping accuracy (e.g., Hall et al 2007). Changes associated with variations in hydrological regimes in wetlands displayed the highest individual class accuracies (80% user's accuracy, 79% producer's accuracy). Areas that experienced multiple non-stand replacing disturbances by the same or different processes were characterized in the annual classifications as a separate class (other). Such areas may have been subject to multiple years of either spruce budworm or forest tent caterpillar defoliation, and/or subsequently experienced significant disturbance (e.g., wind damage, fire, harvesting, including partial harvest operations through salvage cutting, which could also occur after fire). There were significant omission and commission errors between this class and the other non-stand replacing forest change classes.

Generally, the overall and individual classification accuracies in the HFMA test reflect the expected relative distinctiveness and patterns of both stand-replacing and non-stand replacing forest change as represented in Landsat time series data. These classification results confirm that disturbances, when accurately identified by time series change detection (e.g., Franklin et al 2015), can then be accurately classified. In turn, accurate annual change classification, such as obtained by implementing the C2C protocol, provides a sound basis for exploration of forest dynamics and land cover change (Hermosilla et al 2015b). For example, classification of annual change over the time period 1990-2010 in the HFMA revealed that, of the more than 30,000 change objects identified, patterns in year-to-year variability could be associated with wildfire, harvesting, defoliating insect outbreaks and localized seasonal/annual hydrological events. Stand-replacing forest change associated with road-building, forest harvest operations and fire represented two-thirds (about 67%) of the forest change area on an annual basis, while non-stand replacing changes associated with insect outbreaks influenced almost 6% of the area identified as change. A number of small areas were interpreted in the classification as areas of desiccation and secondary forest insect outbreaks. Ephemeral wetland change represented approximately 12% of the change area. And finally, approximately 11% of the area identified as forest change was associated with multiple disturbance events, though multiple disturbances by the same process were not classified separately in this study.

This level of annual forest change classification and interpretation provides a strong foundation for analysis of forest baseline conditions and disturbance, rates of forest change, and sustainability of forest practices. Allocation of change and change types following a hierarchy of categories tied to detectability supports different information needs and focused investigations, given appropriate training data and methods, to further describe change features or conditions of interest (including biotic non-stand replacing disturbances related to forest insects and diseases, and abiotic effects such as those associated with locally-variable hydrological conditions).

5. Conclusion

A standardized Landsat time series protocol C2C has been developed for forest and land cover monitoring and assessment over large-areas and relatively long-time periods in Canada (White et al 2014, Hermosilla et al 2015a,b, 2016). Using this protocol in the Hearst Forest Management Area in northern Ontario, annual forest changes detected using spectral trend analysis (Franklin et al 2015) over two decades (1990-2010) were classified using a machine learning algorithm. Stand-replacing forest changes associated with roads, industrial-scale forest harvesting patterns and wildfires were classified with the highest individual class accuracies and with approximately 90% overall classification accuracy. Four classes of annual non-stand replacing change caused by defoliating insect outbreaks and local hydrological changes (e.g., forest and wetland flooding) were approximately 75% accurate. Areas that experienced multiple non-stand replacing disturbances were identified with higher omission and commission error. In this study, a detailed spatial autocorrelation analysis between the samples is beyond the scope of the current paper but, will be conducted in future research to explore its impact on the classification accuracy. Future research will also examine operational improvements to the use of the time series protocol (e.g., selection of variables, training and validation samples, classifier algorithm, and comparisons to other time series analysis methods), and will consider in greater detail multiple disturbance areas by the same and different processes, additional non-stand replacing forest change processes, and other forest environments.

Acknowledgements:

We thank G. Hobart for his efforts in processing the Landsat data. We also thank the Associate Editor and two anonymous reviewers for their constructive comments, which helped to improve the article. This research was undertaken as part of the "National Terrestrial Ecosystem Monitoring System (NTEMS): Timely and detailed national cross-sector monitoring for Canada" project jointly funded by the Canadian Space Agency (CSA) Government Related Initiatives Program (GRIP) and the Canadian Forest Service (CFS) of Natural Resources Canada. This research was also supported by grants from the Natural Science and Engineering Research Council of Canada (NSERC).

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Table 1. Confusion matrix for disturbance classes (Harvest, Fire, Roads and Non-stand replacing disturbances) using the best RF iteration based on 1090 training area image objects and predictor variables (spectral- and trend-based metrics, and geometrical descriptors).

		Reference						
	Class name	Fire	Harvest	Non-stand replacing	Roads	Sum	User's accuracy (%)	Commission error (%)
Predicted	Fire	267	3	22	5	297	0.90	0.10
	Harvest	2	233	19	4	258	0.90	0.10
	Non-stand replacing	8	5	305	7	325	0.94	0.06
	Roads	3	9	14	184	210	0.88	0.12
	Sum	280	250	360	200	1090		
	Producer's accuracy (%)	0.95	0.93	0.85	0.92	Overall accuracy		90.73%
	Omission error (%)	0.05	0.07	0.15	0.08	Margin of error		± 2.8

Table 2. Confusion matrix for the non-stand replacing disturbance classes (spruce budworm damage, forest tent caterpillar defoliation, ephemeral wetlands, and one class of other disturbances, which includes different multiple events) using the best RF iteration based on 561 training area image objects and predictor variables (spectral- and trend-based metrics, and geometrical descriptors).

	Class name	REFERENCE Spruce Budworm	Forest Tent Caterpillar	Ephemeral Wetlands	Other	Sum	User's accuracy (%)	Commission error (%)
Predicted	Spruce Budworm	65	8	7	21	101	0.64	0.36
	Forest Tent Caterpillar	5	87	9	16	117	0.74	0.26
	Ephemeral Wetlands	10	11	123	10	154	0.80	0.20
	Other	11	14	16	148	189	0.78	0.22
	Sum	91	120	155	195	561		
	Producer's accuracy (%)	0.71	0.73	0.79	0.76	Overall accuracy		75.4%
	Omission error (%)	0.29	0.27	0.21	0.24	Margin of error		± 3.5

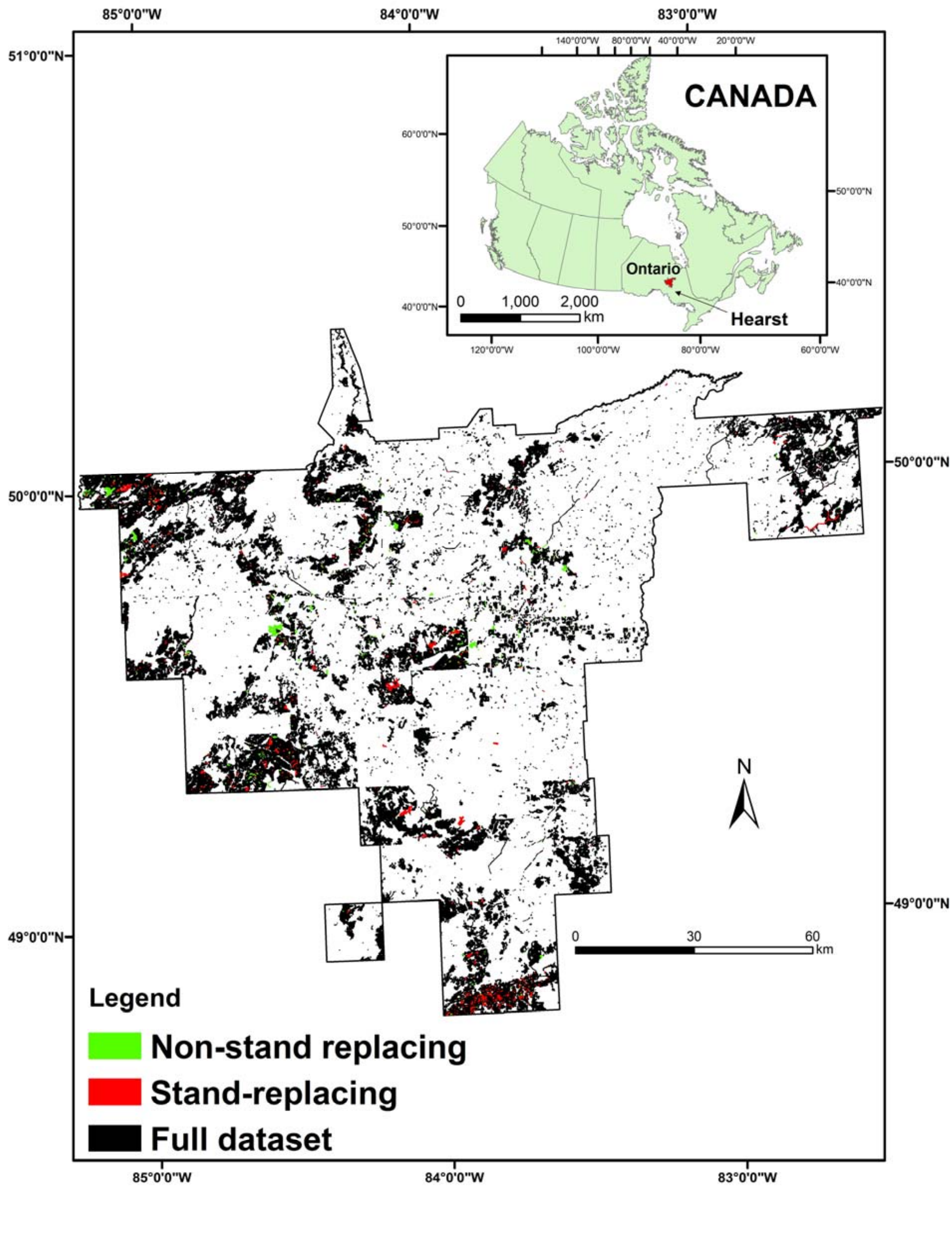

Figure 1. Training and validation sample and full change dataset distribution.