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Remote Sensing of Environment

Confirmation of post-harvest spectral recovery from Landsat time series using measures of forest cover and height derived from airborne laser scanning data



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ARTICLE INFO

Keywords: Landsat

Time series

Regeneration

Recovery

Harvest

ALS

Lidar

Boreal

ABSTRACT

Landsat time series (LTS) enable the characterization of forest recovery post-disturbance over large areas; however, there is a gap in our current knowledge concerning the linkage between spectral measures of recovery derived from LTS and actual manifestations of forest structure in regenerating stands. Airborne laser scanning (ALS) data provide useful measures of forest structure that can be used to corroborate spectral measures of forest recovery. The objective of this study was to evaluate the utility of a spectral index of recovery based on the Normalized Burn Ratio (NBR): the years to recovery, or Y2R metric, as an indicator of the return of forest vegetation following forest harvest (clearcutting). The Y2R metric has previously been defined as the number of years required for a pixel to return to 80% of its pre-disturbance NBR (NBRpre) value. In this study, the Composite2Change (C2C) algorithm was used to generate a time series of gap-free, cloud-free Landsat surface reflectance composites (1985-2012), associated change metrics, and a spatially-explicit dataset of detected changes for an actively managed forest area in southern Finland (5.3 Mha). The overall accuracy of change detection, determined using independent validation data, was 89%. Areas of forest harvesting in 1991 were then used to evaluate the Y2R metric. Four alternative recovery scenarios were evaluated, representing variations in the spectral threshold used to define Y2R: 60%, 80%, and 100% of NBR_{pre}, and a critical value of z (i.e. the year in which the pixel's NBR value is no longer significantly different from NBR_{pre}). The Y2R for each scenario were classified into five groups: recovery within < 10 years, 10-13 years, 14-17 years, > 17 years, and not recovered. Measures of forest structure (canopy height and cover) were obtained from ALS data. Benchmarks for height (> 5 m) and canopy cover (> 10%) were applied to each recovery scenario, and the percentage of pixels that attained both of these benchmarks for each recovery group, was determined for each Y2R scenario. Our results indicated that the Y2R metric using the 80% threshold provided the most realistic assessment of forest recovery: all pixels considered in our analysis were spectrally recovered within the analysis period, with 88.88% of recovered pixels attaining the benchmarks for both cover and height. Moreover, false positives (pixels that had recovered spectrally, but not structurally) and false negatives (pixels that had recovered structurally, but not spectrally) were minimized with the 80% threshold. This research demonstrates the efficacy of LTS-derived assessments of recovery, which can be spatially exhaustive and retrospective, providing important baseline data for forest monitoring.

1. Introduction

Time series of remotely sensed data provide opportunities to characterize forest dynamics over large areas (Banskota et al., 2014). In particular, Landsat time series (LTS) support the characterization of long-term forest recovery (Chu et al., 2016; White et al., 2017); however much remains to be understood concerning the relationship between spectral measures and manifestations of recovery in forest

https://doi.org/10.1016/j.rse.2018.07.004

Received 9 February 2018; Received in revised form 14 June 2018; Accepted 2 July 2018

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structural attributes. Definitions of forest recovery post-disturbance are not universal (Bartels et al., 2016) and often relate to the return of forest structural characteristics following a particular disturbance type (Frolking et al., 2009). Herein, we follow the approach of Frolking et al. (2009) and define recovery as the return of forest structure, quantified by measurable characteristics (e.g. canopy height and cover), against which target thresholds can be applied to indicate when recovery has occurred. In reality, forest recovery is a long-term ecological process, with different functions of a forest returning at different times through the successional process (Spake et al., 2015). Forest recovery post-disturbance is difficult to characterize using data from ground plots alone, particularly over large, remote areas with constraints to forest access (e.g. Canada: Bartels et al., 2016). In nations such as Finland, where intensive forest management practices prevail (Wulder et al., 2007), the capacity for synoptic, spatially-explicit monitoring of forest recovery through time, particularly in the context of a complex land use-land ownership mosaic, is of interest to resource managers and planners (Culotta et al., 2015). Remotely sensed assessments of forest recovery post-disturbance enable assessments of recovery over large spatial extents and different disturbance types (Frolking et al., 2009; Kennedy et al., 2012; Madoui et al., 2015), and provide a framework within which assessments of recovery from ground plot observations may be integrated (Bartels et al., 2016). Moreover remotely sensed assessments of recovery that take advantage of the Landsat archive enable retrospective studies, thereby providing baseline information for monitoring programs (White et al., 2017).

Airborne laser scanning (ALS) data have demonstrated capacity for accurately characterizing forest structure, but are typically limited either in spatial or temporal coverage. In contrast, Landsat data provide both large-area spatial coverage and a temporal archive that extends back to 1982 for 30 m spatial resolution data from the Landsat Thematic Mapper (TM), Enhanced Thematic Mapper Plus (ETM +), and Operational Land Imager (OLI) data. Landsat data have played an important role in the Finnish multi-source National Forest Inventory (MS-NFI) and since 1989, have been used as a means to cost-effectively obtain reliable forest information for areas smaller for which it is not possible to achieve target accuracies with the network of ground plots established for the NFI alone (e.g. a municipality) (Tomppo, 1990). Finland is now generating its 12th MS-NFI (Barrett et al., 2016). Tomppo et al. (2008) suggested that one potential option for enhancing the MS-NFI would be to incorporate historical satellite imagery as a source of additional information on the age and development of forests, citing that information on stand development would be particularly useful in Nordic countries because forest practices have typically been clearcutting (with some required number of retention trees/ha) followed by planting and intensive silviculture (e.g. weeding and cleaning of seedling and sapling stands). A nationwide acquisition of ALS data initiated by the National Land Survey of Finland (NLS) in 2008 has greatly expanded the coverage and availability of ALS data and related forest structural information across the country (Kotivuori et al., 2016).

Assessments of recovery via ground plots are valuable; however, these assessments are spatially and temporally constrained, (Bartels et al., 2016), precluding analyses that are both spatially explicit and spatially exhaustive. ALS data have been used to characterize post-fire forest structure and recovery (Bolton et al., 2015, 2017; Vogeler et al., 2015) and provide the requisite spatial detail and structural characterization; however, a single-date acquisition does not support retrospective assessments of forest structural development over time. Characterization of forest recovery with LTS has become increasingly common with the opening of the Landsat archive in 2008 (Woodcock et al., 2008). While post-disturbance recovery has been explored (Kennedy et al., 2012; Griffiths et al., 2014; Potapov et al., 2015; Frazier et al., 2015 and 2018; Senf et al., 2017), research has demonstrated that the disturbance agent (e.g. wildfire, harvest) influences recovery trajectories (Madoui et al., 2015; White et al., 2017). Characterizations of post-fire recovery with LTS are more common (e.g. Chu

and Guo, 2014), with fewer studies focusing on post-harvest recovery (Schroeder et al., 2007; White et al., 2017). LTS metrics and ALS data can be combined to enhance large-area characterizations of forest structure (Pascual et al., 2010; Ahmed et al., 2014; Zald et al., 2014; Bolton et al., 2018). Moreover, spectral trends derived from LTS improve modeled estimates of forest structure (Pflugmacher et al., 2012) and biomass dynamics (Pflugmacher et al., 2014), and have been demonstrated to improve the characterizations of regenerating forests in temperate (Kennedy et al., 2007) and boreal forest environments (Olsson, 2009).

The temporal length and consistency of LTS are particularly wellsuited to provide supporting information about forest regrowth trends. Schroeder et al. (2007) used LTS to examine the spatial and temporal variability in forest regrowth after clearcutting in western Oregon. To quantify forest regrowth, the authors used estimates of percent tree cover derived from ground plots and interpretation of aerial photographs, which were extrapolated to the LTS using date-invariant regression. The annual percent tree cover data were then grouped into four regrowth classes: little to no, slow, moderate, and fast, and different ecological regions were characterized by the prevalence of each of the regrowth classes. In addition, elevation and potential relative radiation were identified as the main drivers of the different regrowth classes. A similar approach was used by Chu et al. (2016) for assessing post-fire vegetation regrowth, whereby fractional vegetation cover was estimated to assess the return of vegetation. While these relative assessments of recovery can provide useful ecological insights regarding spatial and temporal variations in recovery, these approaches rely on the development of robust models of tree or vegetation cover, and the portability of those models through space and time. Other assessments have relied directly on the spectral metrics (e.g. Pickell et al., 2016; Frazier et al., 2015, 2018). Kennedy et al. (2012) defined an absolute and relative metric of short-term (5-year) recovery derived directly from Normalized Burn Ratio (NBR) values. Griffiths et al. (2014) assessed recovery following stand replacing disturbance in the Carpathians ecoregion using derivatives of the Disturbance Index (Healey et al., 2005). White et al. (2017) characterized both short- (5-year) and long-term (25-year) recovery from harvest and wildfire in a national assessment for Canada's forested ecosystems (~650 Mha) enabled by LTS, adapting the short-term metrics used by Kennedy et al. (2012) and a longer-term metric based on NBR (the Years to Recovery or Y2R metric) used by Pickell et al. (2016).

LTS offer new opportunities to characterize forest dynamics and in particular, provide for the characterization of recovery post-disturbance over large areas; however, there is a knowledge gap concerning how spectral measures of recovery relate to actual manifestations of forest structure (e.g. height and cover). The intensive forest management context in Finland provides a relatively controlled forest environment (i.e. even-aged, limited tree species) and a unique opportunity to explore the relationship between spectral measures of recovery derived from LTS, and actual manifestations of structure, as characterized with ALS data. The overarching goal of this research was therefore to improve our understanding of the linkages between spectral metrics of forest recovery post-harvest-as derived from LTS data-and manifestations of forest structure (height and cover) as measured from ALS data. The specific objectives of this study were threefold: (i) to apply an established image compositing and change detection approach (Composite2Change or C2C) to an area of managed forest in southern Finland and generate a spatially-explicit dataset characterizing forest change (1984-2012); (ii) to validate the detected changes using independent reference data; and (iii) to evaluate the utility and appropriateness of the Y2R spectral recovery metric for assessing the return of forest following harvest in a managed, boreal forest context. This last objective represents the unique contribution of this work: the use of ALS data to corroborate spectral metrics of forest recovery derived from LTS data.

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