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Landsat remote sensing of forest windfall disturbance

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ABSTRACT

Knowing if a forest disturbance is caused by timber harvest or a natural event is crucial for carbon cycle assessments, econometric analyses of timber harvesting, and other research questions. However, while remote sensing of forest disturbance in general is very well developed, discerning between different types of forest disturbances remains challenging. In this work, we developed an algorithm to separate windfall disturbance from clear-cut harvesting using Landsat data. The method first extracts training data primarily based on Tasseled Cap transformed bands and histogram thresholds with minimal user input. We then used a support-vector machine classifier to separate disturbed areas into 'windfall' and 'clear-cut harvests'. We tested our algorithm in the temperate forest zone of European Russia and the southern boreal forest zone of the United States. The forest-cover change classifications were highly accurate (~90%) and windfall classification accuracies were greater than 75% in both study areas. Accuracies were generally higher for larger disturbance patches. At the Russia study site about 60% of all disturbances were caused by windfall, versus 40% at the U.S. study site. Given the similar levels of accuracy in both locations and the ease of application, the algorithm has the potential to fill a research gap in mapping wind disturbance using Landsat data in both temperate and boreal forests that are subject to frequent wind events.

1. Introduction

Forests play an important role in the global carbon cycle and the provision of ecosystem services. Information on where and to what extent forest disturbances occur globally is thus a crucial necessity (Achard et al., 2002; Bonan, 2008). Remote sensing can provide accurate and timely information regarding forest disturbance in many ecoregions at scales ranging from local to global and at many different temporal resolutions (Achard et al., 2006; Baumann et al., 2012; Hansen & DeFries, 2004; Hansen, Stehman, & Potapov, 2010; Healey, Cohen, Yang, & Krankina, 2005; Huang et al., 2010; Potapov, Hansen, Stehman, Pittman, & Turubanova, 2009; Potapov et al., 2012; Zhu, Woodcock, & Olofsson, 2012). Data from Landsat Thematic Mapper (TM) and Enhanced Thematic Mapper Plus (ETM+) instruments have been used for many of these studies because of (1) the favorable combination of spatial, spectral and temporal resolution, (2) the free availability of the data (Wulder, Masek, Cohen, Loveland, & Woodcock, 2012) and, (3) the long-term data record, which continues now thanks to the Landsat Data Continuity Mission (LDCM, Irons, Dwyer, & Barsi, 2012).

In most forest disturbance mapping studies that utilize Landsat data, the derived change products only identify areas of 'forest disturbance', but do not discriminate among different types of disturbances (e.g., Cohen, Fiorella, Gray, Helmer, & Anderson, 1998; Coppin & Bauer, 1994; Ozdogan, in press). This has already been identified as a gap in remote sensing based forest disturbance studies (e.g., Hicke et al., 2012; Kasischke et al., 2013; Masek et al., 2011; Vogelmann, Tolk, & Zhu, 2009). The lack of attribution to the type of disturbance often makes it difficult to interpret forest disturbance maps, especially when these data are used as inputs to carbon budget assessments or econometric analyses. For example, many studies that seek to understand timber harvest trends are forced to equate forest disturbance with harvesting (e.g., Chomitz & Gray, 1996; Wendland et al., 2011). As a result, natural disturbance is erroneously included in harvest estimates, which can lead to overestimation of harvested areas and dampen the significance of actual drivers of forest harvest. Inability to separate forest harvest from natural disturbances also affects studies that assess the effectiveness of protected areas in preventing logging (e.g., Hayes, 2006; Andam, Ferraro, Pfaff, Sanchez-Azofeifa, & Robalino, 2008; Wendland, Baumann, Lewis, Sieber, & Radeloff, in review). From the ecological point of view, information on the type of forest disturbance is important for biomass estimations and for the prediction of post-disturbance succession (Kasischke et al., 2013; Scheller & Mladenoff, 2004). For example, more living biomass remains in place following a windfall event, compared to a clear-cut harvest, which can hinder the establishment of early successional species (Peterson, 2000; Webb & Scanga, 2001; Rich, Frelich, Reich, & Bauer, 2010; Scheller & Mladenoff, 2004).

The most common natural disturbances affecting forests are fire, insect defoliation and windfall (FAO, 2005; FAO, 2010). While remote sensing of fire-related disturbances and insect defoliation has received

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considerable attention in the past (e.g., French et al., 2008; Garcia-Haro, Gilabert, & Melia, 2001; Patterson & Yool, 1998; Pereira & Setzer, 1993; Roder, Hill, Duguy, Alloza, & Vallejo, 2008; Schroeder, Wulder, Healey, & Moisen, 2011; Townsend et al., 2012; Van Wagtendonk, Root, & Key, 2004), only a handful of studies have focused on identifying and mapping windfall disturbances. In general, the existing studies can be categorized into two themes. The first category focuses on monitoring the impacts of tropical storms on forest structure using multispectral imagery or radar data (e.g. Cheung, Pan, Gu, & Wang, 2013; Negron-Juarez, Baker, Zeng, Henkel, & Chambers, 2010; Nelson, Kapos, Adams, Wilson, & Braun, 1994; Ramsey, Rangoonwala, Middleton, & Lu, 2009; Ramsey, Werle, Lu, Rangoonwala, & Suzuoki, 2009; Wang & Xu, 2010). The second area of focus is severe storm (including tornados) damage on forests of continental interiors, which are characterized by smaller affected areas but high intensity disturbances, such as the Boundary Waters Blowdown in the Greater Border Lakes Region (USA) in 1999 (Rich et al., 2010; Wolter et al., 2012). However, while these studies were successful in mapping the damage caused by each particular storm, they did not include developing a specialized, and potentially universal, method to separate wind-related change from other disturbances.

The Disturbance Index (DI, Healey et al., 2005) is an example of a universal method. The algorithm has been developed to detect areas of forest disturbance, and has been tested in a wide range of forest biomes including the Pacific Northwest (USA), the St. Petersburg and other locations in Russia, South-Sudan and Uganda and the conterminous United States (Healey et al., 2005; Masek et al., 2008; He et al., 2011; Gorsevski, Kasischke, Dempewolf, Loboda, & Grossmann, 2012; Sieber et al., 2013). One reason for the success of the DI is its use of the Tasseled Cap transformation that convert Landsat bands into brightness', 'greenness', and 'wetness' measures to describe the variations in soil background reflectance, vegetation vigor, and vegetation senescence, respectively (Crist & Kauth, 1986; Kauth & Thomas, 1976). The success of the Tasseled Cap bands in the DI across different study regions suggests that a windfall classification algorithm based on the same standardized bands might be successful as well across different regions throughout the world.

Our goal here was to develop an algorithm to distinguish windfall disturbance from forest harvests with Landsat data in two different locations. Our specific objectives were to:

1 create a map of forest and forest disturbance using established methods from the literature,
2 develop an algorithm to separate the areas of forest-disturbance into windfall disturbance and clear-cut harvests,
3 test our algorithm in two study regions, (1) the temperate zone of European Russia and (2) the southern boreal forest zone of the United States.

2. Methods

2.1. Study area

Our first study site is located in the temperate zone of European Russia (Landsat Path/Row 177/019, Fig. 1 bottom right). Temperate coniferous, broadleaf, and mixed forests dominate the landscape with Norway spruce (*Picea abies*) and Scots pine (*Pinus sylvestris*) being the most abundant coniferous species. Major deciduous species include aspen (*Populus tremula*), gray alder (*Alnus incana*), and birch (*Betula pendula*). Commercial harvests are widespread in the region, because the Russian forestry sector is growing and western forest companies are increasing their investments in mills to exploit Russia's vast timber resources (Mutanen & Toppinen, 2007). Besides commercial harvests, the region experiences frequent natural disturbance events. Specifically, the study region experienced two storms that occurred in October 2009 and July 2010 (Koroleva & Ershov, 2012), which were studied and mapped in detail by the Russian Forest Health Center (Krylov, Malahova, & V., 2012).

The second study site is located in the southern boreal forests in northern Minnesota (USA) (Landsat Path/Row 025/028, Fig. 1, bottom left). The region is characterized by a mixture of glacial lakes and wetlands. Forest species in the region include early successional species, such as jack pine (*Pinus banksiana*), red pine (*Pinus resinosa*), or aspen (*Populus tremuloides*), as well as late successional species like white cedar (*Thuja occidentalis*) or balsam fir (*Abies balsamea*) (Frelich & Reich, 1995; Rich et al., 2010). In 1999, the region experienced a large infrequent wind disturbances event, which is referred as the Boundary Waters Blowdown (or the Boundary Waters Canadian Derecho). The storm occurred between July 4th and 5th 1999 and lasted 22 h. It traveled over 2000 km at an average pace of around 95 km/h, and with wind gusts of over 160 km/h. The storm caused over 1500 km^2 of considerable forest damage (Price & Murphy, 2002), and has been a research subject in the past (Rich et al., 2010; Wolter et al., 2012).

2.2. Image pre-processing

At both locations we analyzed Landsat data from the year before and the year after the windfall event. Our temporal frames were 1998–2000 for the U.S. site and 2009–2011 for the Russia site. Imagery for both study sites were pre-processed by converting digital numbers into surface reflectance using the Landsat Ecosystem Disturbance Adaptive Processing System (LEDAPS) algorithm (Masek et al., 2006). Cloud-free images were available for both time points at the U.S. site, but not for the Russia site. Therefore, we selected images with the least amounts of clouds (hereafter called the base-image) and gap-filled them using other Landsat scenes from the same growing season (i.e., late May to August; 2009 and 2011, respectively, Table 1). Gap-filling was accomplished by first masking clouds and cloud shadows in each image using FMask (Zhu & Woodcock, 2012), applying conservative threshold values to ensure that a maximum of clouds and cloud shadows were detected. Afterwards, we filled the gaps of our base-image using all other images from the respective growing season. We ensured that images located at the edge of a growing season (i.e., late May) were chosen last to fill gaps in the base-image. We thus minimized potential influences of a late spring onset that sometimes can lead to class confusions in forest/non-forest classifications. The result was a nearly cloud-free image composite for both time points (2009 and 2011).

2.3. Forest/non-forest classification

For both study sites, we classified the pre-disturbance image (1998 for the U.S. site, and 2009 for the Russia site) into 'forest' and 'non-forest' using a training data set generated automatically using the dark object approach (Huang et al., 2008). More specifically, we searched for the peak within a local histogram of Landsat's red band (Band 3). In the absence of non-vegetated dark objects, such as water or dark soil, pixels to the left of the peak can be considered forest pixels (Huang et al., 2008). We removed non-vegetated dark objects by applying a consistency check using the globally available Moderate-Resolution Imaging Spectroradiometer (MODIS) vegetation continuous field product (VCF, Hansen et al., 2006) with a threshold value of 40%. Dark pixels passing this consistency check were then collected within a group of confident forest samples and used to calculate the Integrated Forestness Index (IFI):

$$IFI = \sqrt{\frac{1}{NB}\sum_{i=1}^{NB}\left(\frac{b_{pi}-\overline{b}_i}{SD_i}\right)^2} \qquad (1)$$

where $\overline{b_i}$ and SD_i are the mean and standard deviation of the candidate forest pixels within that image for band i, b_{pi} is the spectral value for pixel p in band i, and NB is the number of bands (Huang et al., 2008).