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Characterizing spatial-temporal patterns of landscape disturbance and recovery in western Alberta, Canada using a functional data analysis approach and remotely sensed data

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ABSTRACT

Landscape regionalization approaches are frequently used to summarize and visualize complex spatial patterns, environmental factors, and disturbance regimes. However, landscapes are dynamic and contemporary regionalization approaches based on spatial patterns often do not account for the temporal component that may provide important insight on disturbance, recovery, and how ecological processes change through time. The objective of this research was to quantify spatial patterns of disturbance and recovery over time for use as inputs in a regionalization that characterizes unique spatial-temporal trajectories of disturbance in western Alberta, Canada. Cumulative spatial patterns of disturbance, representing the proportion, arrangement, size, and number of disturbances, and adjusted annually for spectral recovery, were quantified in 223 watersheds using a Landsat time series dataset where disturbance events are detected and classified annually from 1985 to 2011. Using a functional data analysis approach, disturbance patterns metrics were modelled as curves and scores from a functional principal components analysis were clustered using a Gaussian finite mixture model. The resulting eight watershed clusters were mapped with mean curves representing the temporal trajectory of disturbance. The cumulative mean disturbance pattern metric curves for each cluster showed considerable variability in curve amplitude which generally increased markedly in the mid-1990's, while curve amplitude remained low in parks and protected areas. A comparison of mean curves by disturbance type (e.g., fires, harvest, non-stand replacing, roads, and well-sites) using a functional analysis of variance showed that anthropogenic disturbance contributed substantially to curve amplitude in all clusters, while curve amplitude associated with natural disturbances was generally low. These differences enable insights regarding how cumulative spatial disturbance patterns evolve through time on the landscape as a function of the type of disturbance and rates of recovery.

1. Introduction

Terrestrial ecosystems are subject to a range of natural and anthropogenic disturbances that influence landscape dynamics and heterogeneity. In North America, the frequency, extent, and severity of natural disturbances, including forest fires (Bourbonnais et al., 2014; Flannigan et al., 2006; Stocks et al., 2002), insect infestation and disease (Kurz et al., 2008; Volney and Hirsch, 2005), and environmental impacts such as wind and drought (Dale et al., 2001), has been increasing due to anthropogenic influences and climate change (Turner, 2010). Similarly, anthropogenic activities and pressures on many terrestrial ecosystems are growing (Venter et al., 2016), and distur-

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bances such as forest harvest (Masek et al., 2011; Pickell et al., 2014), road network development (Forman and Alexander, 1998; Trombulak and Frissell, 2000), and energy development and mining (Pickell et al., 2014, 2015; White et al., 2011), contribute substantially to land use change (DeFries et al., 2004; Pickell et al., 2015) and landscape fragmentation (Pickell et al., 2016a; Wulder et al., 2008a). Cumulatively, the extent and severity of disturbance influences ecological processes, and is temporally dynamic given post-disturbance recovery, regeneration, and succession (Bartels et al., 2016; Frazier et al., 2015). As such, monitoring and quantifying how spatial patterns of landscape disturbance vary over time can highlight how ecological processes are influenced by disturbance and recovery, as well as forest and land management (Fraser et al., 2009; Wulder et al., 2009).

Methods for detecting and attributing disturbance from remotely sensed time series datasets provide opportunities to quantify spatial patterns and temporal dynamics of landscape disturbance, change, and recovery. While disturbance detection and land cover change have been quantified using a variety of remote sensing technologies, Landsat data have been used extensively due to the longevity and spatial resolution of the available data (Hansen and Loveland, 2012; Wulder et al., 2008b). The 30 m spatial resolution of Landsat data allows for the capture of disturbances at human scales; that is, landscape alterations that are the result of a given management or land use decision can be discerned over large areas in a systematic and repeatable fashion (Wulder et al., 2012).

Detection of land cover changes has long been a primary focus of methodological development (Jönsson and Eklundh, 2004; Lu et al., 2004). Contemporary change detection approaches have extended bi-temporal scene comparisons (e.g., Coppin et al., 2004) to include dense time series of remotely sensed imagery allowing more detailed land cover change detection and characterization (Banskota et al., 2014; Hermosilla et al., 2015a; Hilker et al., 2011; Huang et al., 2010; Kennedy et al., 2007). Chiefly, bi-temporal scene comparison allows for capture of binary change, while the capture of change using more than two dates allows for insights on disturbance aspects such as rates and persistence combined with directionality, as well as overall pre- and post-disturbance trends (Gillanders et al., 2008). In part, change detection approaches have been facilitated by the rapid development of image compositing techniques, resulting in gap-free time series of spectral reflectance values (Griffiths et al., 2013; Hermosilla et al., 2015a; Hilker et al., 2009; Roy et al., 2010; White et al., 2014a). The temporal dimension of products generated from remotely sensed data can be leveraged to develop new hypotheses on disturbance recovery and land cover change (Franklin et al., 2015; Hansen et al., 2011; Hermosilla et al., 2015b, 2016; Pickell et al., 2016b; Roy et al., 2010).

Landscape regionalization approaches, where geographic entities are grouped based on common factors in order to simplify and explain complex landscape and environmental dynamics (Hargrove and Hoffman, 2004), are common in ecology (e.g., Coops et al., 2009; Fitterer et al., 2012; Thompson et al., 2016). While regionalization approaches have been developed to characterize spatial patterns of landscape disturbance (Long et al., 2010) and land use (Zurlini et al., 2007) using landscape pattern metrics (e.g., Boots, 2006; Turner, 1990; Turner, 2005), the temporal dynamics of disturbance and recovery are often left unaccounted which can influence the interpretation of resulting patterns (Gómez et al., 2011, 2015; Pickell et al., 2016a). Further, characterizing spatial-temporal patterns of landscape disturbance and recovery is difficult as multivariate time series data are frequently high-dimensional (Liao, 2005).

Methods in functional data analysis (FDA) are specifically designed to characterize data that are multivariate, temporally structured, and high-dimensional (Morris, 2015; Ramsay et al., 2009). In the FDA framework, the fundamental object underlying observed data are functions, typically assumed smooth in some sense. Within this context, discrete time series observations are considered to arise through the regular sampling of a single smooth function (i.e., curve), rather than thought of as a realization from a multivariate distribution, representing the underlying process (Ramsay and Silverman, 2005; Ramsay et al., 2009). Statistical inference then involves reconstruction of the underlying function based on the noisy time series data, and subsequently methods including clustering (Hitchcock and Greenwood, 2015; Jacques and Preda, 2014), principal components analysis (Frøslie et al., 2013; Shang, 2014), analysis of variance (Cuevas et al., 2004; Ramsay et al., 2009), and regression (Morris, 2015) have been extended to the functional data setting. By modelling multivariate disturbance time series data using the FDA paradigm, landscape pattern metrics quantified annually can be characterized as functions (i.e., curves) representing disturbance as a temporally continuous process, rather than a discrete state (Frazier et al., 2015; Frolking et al., 2009; Gómez et al., 2011; Kennedy et al., 2010).

The goal of our research is to characterize disturbance as temporally dynamic, allowing us to quantify and map cumulative patterns of disturbance while simultaneously accounting for recovery. To do so, we develop an FDA regionalization of landscape disturbance in western Alberta, Canada from 1985 to 2011 using Landsat disturbance time series data (Hermosilla et al., 2015a, 2015b, 2016). The region represents a complex and shifting mosaic of natural ecosystems and land use strategies influenced by extensive cumulative natural and anthropogenic disturbance (Pickell et al., 2015; White et al., 2011). Characterizing landscape disturbance patterns as curves, our regionalization identifies unique temporal trajectories of cumulative disturbance patterns that represent underlying distributions and temporal trajectories of specific natural and anthropogenic disturbance types, including forest fires, forest harvest and roads. The regionalization provides an effective means for quantifying and visualizing complex spatial-temporal patterns of disturbance and recovery and highlights the utility of FDA approaches when working with multivariate remote sensing time series data.

2. Materials and methods

2.1. Study area

The study area is approximately 158,000 km^2 in western Alberta, Canada (Fig. 1). Monitoring of landscape disturbance in the region is critical due to the overlap between on-going resource extraction activities and habitat of threatened and endangered species in the region including grizzly bears (Festa-Bianchet, 2010) and mountain caribou (COSEWIC, 2014). Watersheds (n = 223), were selected as the landscape unit of analysis for the regionalization and defined using heights of land along major watercourses (White et al., 2011), and as such correspond to fifth-level catchments. Watersheds are commonly selected as an environmentally relevant landscape unit for monitoring forest and land cover changes (Wulder et al., 2009), as well as monitoring environmental variability and habitat security (Noss et al., 2002). The study area is topographically complex, with elevations ranging from 450 m to 3500 m above sea level. Major ecosystems include prairies to the east transitioning to coniferous and mixed-wood forests, and high montane sub-alpine and alpine landscapes in the west. Resource extraction activities in the region include forestry, oil and gas exploration, mining, and agriculture, which are all serviced by an extensive road network. A network of parks and protected areas, where resource extraction is limited, exists primarily in the western mountainous area. Important natural forest disturbances include forest fires (Gralewicz et al., 2012a), insect infestation (Safranyik et al., 2010), and non-stand replacing disturbances of variable magnitude (e.g., wind, drought, stress).

2.2. Data

Landscape disturbance from 1985 to 2011 was characterized by Hermosilla et al. (2015a, 2015b, 2016) in a recently developed