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A functional data analysis approach for characterizing spatial-temporal patterns of landscape disturbance and recovery from remotely sensed data

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ABSTRACT

Contemporary landscape regionalization approaches, frequently used to summarize and visualize complex spatial patterns and disturbance regimes, often do not account for the temporal component which may provide important insight on disturbance, recovery, and change in ecological processes. The objective of this research was to employ novel statistical approaches in functional data analysis to quantify and cluster spatial-temporal patterns of landscape disturbance and recovery in 223 watersheds using a Landsat disturbance time series from 1985 – 2011 in western Alberta, Canada. Cumulative spatial patterns of disturbance, representing the proportion, arrangement, size, and number of disturbances per watershed, were modelled as functions and scores from a functional principal component analysis were clustered using a Gaussian finite mixture model. The resulting eight watershed clusters were mapped with mean functions representing unique temporal trajectories of disturbance and recovery. There was considerable variability in disturbance amplitude among the clusters which increased markedly in the mid-1990's while remaining low in parks and protected areas. The regionalization highlights unique temporal trajectories of disturbance and recovery driven by anthropogenic and natural disturbances and enables insight regarding how cumulative spatial disturbance patterns evolve through time.

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 and insect infestations, has been increasing due to anthropogenic influences and climate change (Turner, 2010). Similarly, anthropogenic activities and anthropogenic pressures on many terrestrial ecosystems are growing as resource extraction activities, including forest harvest, road network development, and energy development and mining contribute to land use change and landscape fragmentation (Pickell et al., 2016). Cumulatively, landscape disturbance is temporally dynamic given post-disturbance recovery, regeneration, and succession. As such, monitoring and quantifying how spatial patterns of natural and anthropogenic landscape disturbance change over time is critical for understanding how ecological processes are influenced by disturbance and recovery.

Change detection and attribution of disturbance from remotely sensed time series data provide opportunities to develop new hypotheses on disturbance recovery and land cover change. The spatial resolution and longevity of the Landsat mission, in particular, allows detection of landscape alterations that are the result of a given management or land use decision over large areas in a systematic fashion (Wulder et al., 2012). While regionalization approaches, where geographic entities are grouped based on common factors to summarize complex landscape and environmental factors (Hargrove and Hoffman 2004), have been developed to characterize spatial patterns of landscape disturbance (e.g., Long et al., 2010), the temporal dynamics of disturbance and recovery are often left unaccounted which can influence interpretation of resulting patterns (Pickell et al., 2016).

The goal of this study is to characterize disturbance as a temporally dynamic, allowing us to quantify and map cumulative patterns of landscape disturbance while simultaneously accounting for recovery. To this end, we develop a novel functional data analysis regionalization of landscape disturbance in 223 watersheds in western Alberta, Canada from 1985 to 2011 using Landsat disturbance time series data (Hermosilla et al., 2015). Methods in functional data analysis (FDA) are specifically designed to characterize multivariate high-dimensional time series data (Ramsay & Silverman, 2005). Using the FDA framework, our regionalization identifies unique temporal trajectories of cumulative disturbance patterns representing underlying distributions and spatial-temporal dynamics of specific natural and anthropogenic disturbance types, including forest fires, harvest, and roads (Bourbonnais et al., 2017).

2. Methods and Data

2.1 Landsat data and disturbance pattern metrics

The study used a novel Canada-wide landscape disturbance time series derived from a best-available pixel Landsat data product where disturbances, including forest harvest, oil and gas well-sites, roads, forest fires, and non-stand replacing disturbances (e.g., insects and drought) were detected and attributed annually from 1985 – 2011 (Hermosilla et al., 2015). Using the Landsat disturbance time series, spatial patterns of landscape disturbance were quantified annually using the proportion area disturbed, the probability of disturbance adjacency, the mean disturbance patch area, and the number of disturbance patches in 223 watersheds in western Alberta. Watersheds were selected as the landscape unit of analysis for the regionalization as they are commonly used as an environmentally relevant scale for monitoring forest and land cover changes (Wulder et al., 2009). The disturbance pattern metrics were adjusted annually to account for recovery by comparing the normalized burn ratio (NBR = (B4-B7)/(B4+B7) where B4 and B7 correspond to Landsat bands 4 – near-infrared – and 7 – short-wave infrared, respectively) from the pre- and post-disturbance periods (Key & Benson, 2006). A disturbance pixel was considered recovered, and subsequently masked from the annual disturbance pattern metrics, when the post-disturbance NBR values reached 80% of the mean pixel NBR values from the two years preceding disturbance (Pickell et al., 2016).

2.2 Functional data analysis regionalization

In the FDA framework, discrete time series observations (i.e., disturbance pattern metrics) are considered to arise through the regular sampling of a smooth function (i.e., curve) rather than thought of as a realization from a multivariate distribution (Ramsay & Silverman, 2005). Following the FDA approach, the time series of discrete disturbance pattern metrics in each watershed were converted to curves using B-splines as the basis function. We used a functional principal component analysis (FPCA), which estimates a set of eigenvalue-eigenfunction pairs, to quantify the primary modes of temporal variation among the curves for each of four disturbance pattern metrics (Ramsay & Silverman, 2005). For each of the four disturbance pattern metrics, we computed the minimum number of FPCA scores, representing the difference from the mean disturbance pattern curve, required to explain 90% of the functional variance in the curves. The FPCA scores (n = 11), which represent the primary modes of temporal variation in the disturbance pattern metric curves, formed the basis for our regionalization. We regionalized watersheds with common disturbance patterns by clustering the FPC scores using Gaussian finite mixture models with the optimal number of groups selected using the negative of the Bayesian Information Criterion (Fraley & Raftery, 2002). The clustered watersheds were then mapped and compared using the mean disturbance pattern metric curves by region. We further explored variability in pattern metrics of attributed disturbances (fire, harvest, roads, well-sites, and non-stand replacing) for each watershed cluster using a functional analysis of variance (FANOVA) by comparing the mean curves based on shape and temporal variability (Ramsay & Silverman, 2005).

3. Results

Three FPCA scores were required to explain 90% of the variance in the proportion disturbance, probability of disturbance adjacency, and mean disturbance patch area, and two scores for the number of disturbance patches (Figure 1). Amplitude in the first FPCA score, representing the greatest deviation of the curve from the mean, generally increased markedly beginning in the mid-1990's characterizing differing disturbance pattern trajectories resulting from a rapid increase in resource extraction and industrial activity in the region.

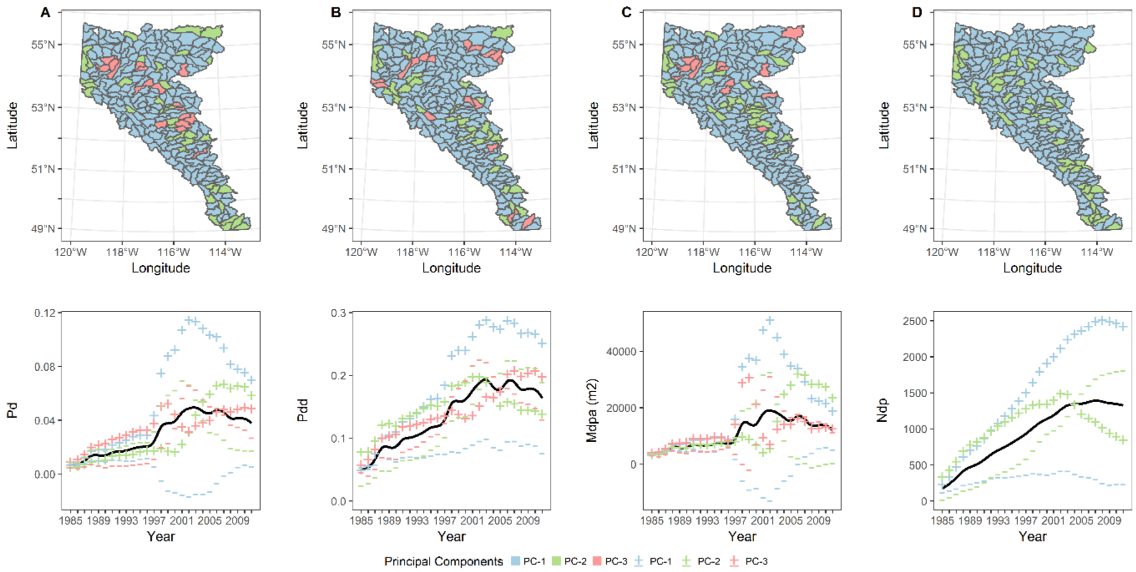

Figure 1. Functional principal components analysis (FPCA) for disturbance pattern metric curves of proportion disturbance (A), probability of disturbance adjacency (B), mean disturbance patch size (C) and number of disturbance patches (D). The upper plot maps the score with the highest absolute value for each watershed. The lower panel shows the mean of the fitted disturbance pattern metric curve (solid black line) and how the amplitude of the mean curve varies if the FPCA curve is added (+) or subtracted (-).

The Gaussian finite mixture model incorporating the eleven FPCA scores with the greatest support (BIC = -2095.35) resulted in eight disturbance pattern regions (Figure 2). Watersheds in clusters 1 (35.92%), 5 (16.33%), and 4 (13.46%) represented the greatest proportion of the study area. The amplitude (i.e., vertical) and phase (i.e., horizonal) variability of the four-disturbance pattern metric mean curves characterized periods of increasing disturbance (i.e., increasing curve amplitude) and spectral recovery (i.e., decreasing curve amplitude) among the watershed regions. Watersheds in clusters 1, 2, 3, 5, and 6 had increasing amplitude throughout the study period with notable recovery beginning circa 2005. Conversely, regions occurring primarily in parks and protected areas (clusters 4, 7, and 8) had the lowest overall disturbance amplitude. Interestingly, while the mean proportion disturbance, probability of disturbance adjacency, and mean disturbance patch size curves demonstrated periods of recovery (i.e., periods of decreasing amplitude in the curve), the number of disturbance patches generally increased over time suggesting spatial variability in recovery may result in a complex spatial mosaic of patches in different successional states (Gómez et al., 2011).

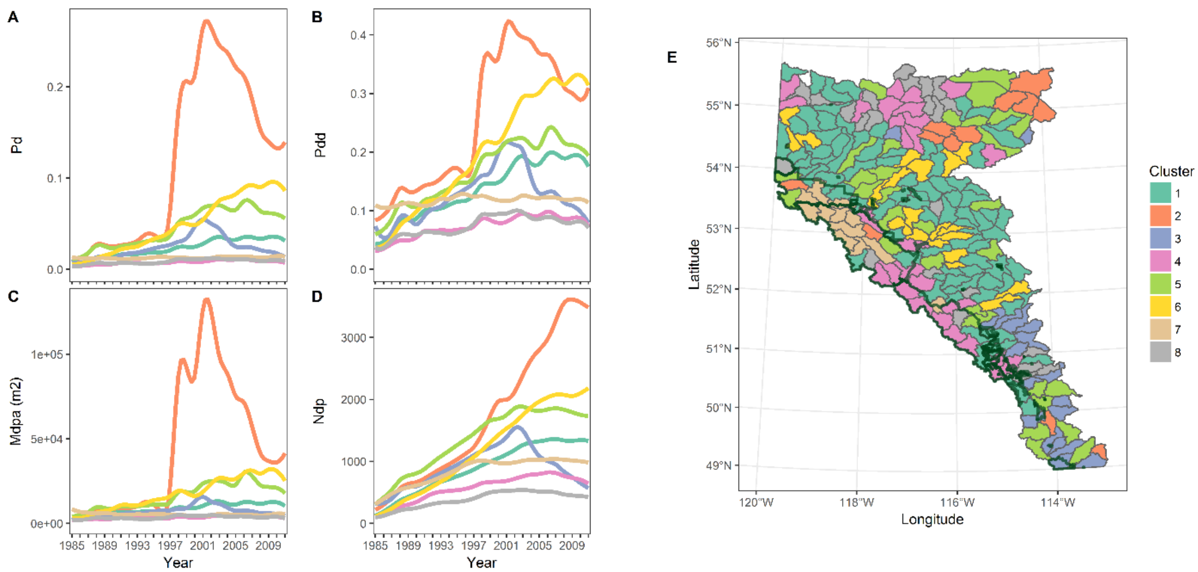

Figure 2. Mean curves by cluster for the proportion disturbance (A), the probability of disturbance adjacency (B), the mean disturbance patch area (C), and the number of disturbance patch (D) pattern metrics. Each mean curve is associated with the watersheds mapped by cluster membership (E). Parks and protected areas are shown in green.

The watershed clusters also revealed variability in the amplitude and phase of the mean disturbance pattern metrics for the attributed disturbance types compared using FANOVA (Figure 3). Mean forest fire curves were significantly different ($p < 0.05$) among the watershed clusters, with large forest fires prevalent in clusters 2 and 5. Trajectories representing the mean proportion area disturbed and number of disturbed patches for forest harvest, roads, and well-sites were also significantly different among the clusters, and had the greatest amplitude in clusters 6, 1, 5, and 2 representing watersheds primarily outside of parks and protected areas.

4. Conclusion

While piece-wise properties of curves have been employed to detect and quantify disturbance patterns (Gómez et al., 2011), modelling patterns of landscape disturbance and recovery as a single continuous function can reveal properties of the underlying ecological processes and how patterns of landscape disturbance evolve over a continuum (Pickell et al., 2016). However, it is difficult to quantify landscape disturbance cumulatively and to account for the temporal dynamics of disturbance and recovery, as well as the interaction of multiple sources of natural and anthropogenic disturbance. Using the novel FDA approach described here, regional spatial-temporal disturbance patterns can be interpreted through representative disturbance trajectories which illuminate the different disturbance processes and indicate where and when anthropogenic disturbance is the dominant driver of observed patterns in the study area. As new time series of disturbance and land cover data become increasingly available, FDA-based approaches can be useful for quantifying and summarizing complex spatial-temporal landscape patterns.

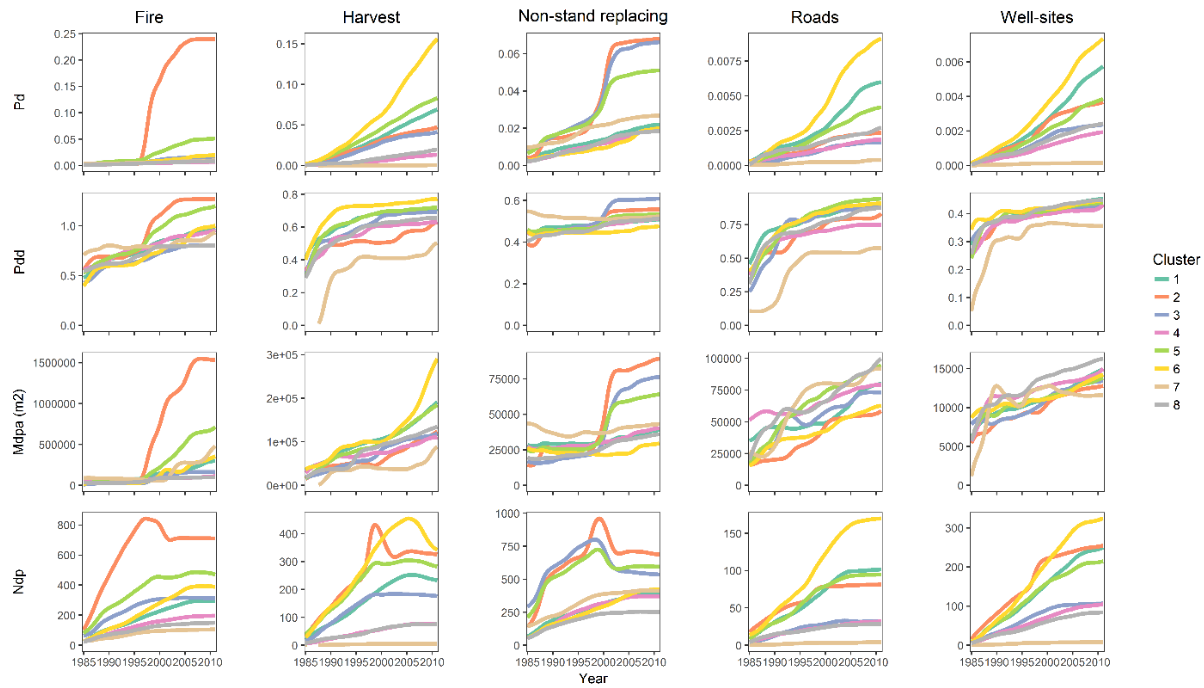

Figure 3. Results of the functional analysis of variance showing mean curves of the proportion area disturbed (Pd), probability of disturbance adjacency (Pdd), mean disturbance patch area (Mdpa), and number of disturbance patches (Ndp), for the attributed disturbances (fire, harvest, non-stand replacing, roads, and well-sites) by cluster.

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