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Multi-temporal LiDAR and Landsat quantification of fire-induced changes to forest structure

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ABSTRACT

Measuring post-fire effects at landscape scales is critical to an ecological understanding of wildfire effects. Predominantly this is accomplished with either multi-spectral remote sensing data or through ground-based field sampling plots. While these methods are important, field data is usually limited to opportunistic post-fire observations, and spectral data often lacks validation with specific variables of change. Additional uncertainty remains regarding how best to account for environmental variables influencing fire effects (e.g., weather) for which observational data cannot easily be acquired, and whether pre-fire agents of change such as bark beetle and timber harvest impact model accuracy. This study quantifies wildfire effects by correlating changes in forest structure derived from multi-temporal Light Detection and Ranging (LiDAR) acquisitions to multi-temporal spectral changes captured by the Landsat Thematic Mapper and Operational Land Imager for the 2012 Pole Creek Fire in central Oregon. Spatial regression modeling was assessed as a methodology to account for spatial autocorrelation, and model consistency was quantified across areas impacted by pre-fire mountain pine beetle and timber harvest. The strongest relationship (pseudo-$r^2 = 0.86$, $p < 0.0001$) was observed between the ratio of shortwave infrared and near infrared reflectance (d74) and LiDAR-derived estimate of canopy cover change. Relationships between percentage of LiDAR returns in forest strata and spectral indices generally increased in strength with strata height. Structural measurements made closer to the ground were not well correlated. The spatial regression approach improved all relationships, demonstrating its utility, but model performance declined across pre-fire agents of change, suggesting that such studies should stratify by pre-fire forest condition. This study establishes that spectral indices such as d74 and dNBR are most sensitive to wildfire-caused structural changes such as reduction in canopy cover and perform best when that structure has not been reduced pre-fire.

1. Introduction

Remote sensing plays a critical role in allowing resource managers and scientists to assess fire effects across landscapes (Lentile et al., 2006). The quantification of fire effects is critical to understanding ecological impacts of fire, including evaluating ecosystem rehabilitation needs (Hessburg et al., 2015; Turner et al., 1994), mitigating secondary fire effects (e.g., flooding and erosion) (Moody et al., 2008; Robichaud et al., 2009), monitoring anomalies and trends in ecological recovery (Cansler and Mckenzie, 2014; Eidenshink et al., 2007; Miller et al., 2009), and quantifying carbon balance (Meigs et al., 2009; Randerson et al., 2012). In light of the observed and projected increases in wildfire activity under anthropogenic climate change (Abatzoglou and Williams, 2016; Barbero et al., 2015), the ability to accurately quantify long-term carbon stocks is necessary for understanding biosphere-atmosphere feedbacks (Li et al., 2014). However, accurate spatiotemporal quantification of fire effects has been a key limitation, which the remote sensing community has worked to address. While considerable advances have been made in relating observed changes associated with fire effects to remote sensing data (Disney et al., 2011; Lentile et al., 2006; Smith et al., 2016b), there are still knowledge gaps and several known sources

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of uncertainty that can lead to extensive errors when applied to regional assessments (Kolden et al., 2015; Roy et al., 2006; Smith et al., 2016 a,b).

Most notably, considerable disconnects exist between burn severity maps produced from relatively high-resolution, passive, spectral reflectance data, and observed fire-induced changes in forest structure that are readily related to aboveground carbon stocks and other metrics of interest to the broader science community (Kolden et al., 2015; Lentile et al., 2006). The products developed through the transformation of post-fire reflectance data to spectral indices are interpreted as burn severity, a term that does not currently have an agreed-upon biometric definition (Keeley, 2009; Lentile et al., 2006). These products frequently include the Normalized Burn Ratio, delta NBR (dNBR; Key and Benson, 2006), and the Relative dNBR (RdNBR; Miller and Thode, 2007); the latter two indices are calculated as a national United States product by the Monitoring Trends in Burn Severity (MTBS) project (Eidenshink et al., 2007). Burn severity maps are useful for a range of management needs, and have been widely utilized for operational burned area rehabilitation efforts. However, they have also been used for research efforts that require more robust data inputs, such as to model pyrogenic emissions (Meigs et al., 2011), despite limited mechanistic validation of the products (Kolden et al., 2015; Sparks et al., 2015).

The primary measure utilized to calibrate such indices and products is the Composite Burn Index (CBI) (Key and Benson, 2006), a set of observations of surface changes inferred without pre-fire data and subject to several limitations (Lentile et al., 2009). Measurements are ocularly estimated (Lentile et al., 2009; Morgan et al., 2014; Zhu et al., 2006), and are aggregated across vertical strata to a comprehensive, unitless severity score that correlates poorly to both individual biometrics of interest and spectral reflectance of the top-most surface (De Santis and Chuvieco, 2007; Hudak et al., 2007). CBI protocol includes subjectively reconstructing estimates of pre-fire conditions in the post-fire environment based on unburned areas in the vicinity of the plot (i.e., no pre-fire data are collected), but it suggests placing plots amidst relatively homogeneous areas of fire severity. In stand-replacing fire regimes it is not uncommon to have plots fall amid large areas of high severity with no nearby indicators of pre-fire condition. This approach was developed for management needs and provides data sufficient for many management applications, but also yields data of unknown accuracy that are extremely difficult, if not impossible, to verify (Lentile et al., 2006; Morgan et al., 2014; Smith et al., 2016b; Zhu et al., 2006). CBI has been the standard for burn severity assessment for over a decade, but as new data types become available (e.g., LiDAR) and more existing field plots are burned in fires, more robust field methods should be developed to overcome CBI limitations.

The difficulty in quantifying fire-induced change without pre-fire measurements extends beyond the CBI protocol. There have been a few research opportunities where fire burned through permanent monitoring plots that were subsequently assessed (Bishop et al., 2014; Cocke et al., 2005; Lutz et al., 2016; Wimberly and Reilly, 2007); however, these studies have relied on small numbers of burned plots to represent change over a large area. Long-term monitoring plots associated with the Forest Inventory and Analysis (FIA) project (Gillespie, 1999) have burned with greater frequency in recent years, but the re-measurement intervals between FIA collections (5–10 years) can lead to considerable disconnects between the fire event and the post-fire re-visit, reducing the visibility and magnitude of those effects when data collection does occur (Whittier and Gray, 2016). The lack of pre-fire observations for the majority of field data utilized to calibrate burn severity spectral indices leads to inconsistency between the remote sensing measures that quantify change between pre- and post-fire acquisitions and field calibration measures that are limited to post-fire observations (Smith et al., 2016b). Measuring only the post-fire environment cannot adequately represent the effects of fire, because it fails to capture the magnitude of change, whether the observed changes are in fact directly caused by the fire, or if another disturbance event is also contributing (Roy et al., 2013; Smith et al., 2010; Smith et al., 2016b). Without the development of physical linkages between spectral data and quantitative measures of forest structure, errors in carbon quantification will extrapolate through models, propagating errors (Kolden et al., 2015); to-date, only a limited number of studies have sought to relate radiometric datasets to mechanistic changes in vegetation following fires (Chuvieco et al., 2006; De Santis et al., 2009; De Santis and Chuvieco, 2007; Disney et al., 2011; Smith et al., 2016b).

The increasing acquisition frequency of airborne Light Detection and Ranging (LiDAR) data over relatively large areas offers a potential alternative mode of measuring fire-induced ecological change and calibrating reflectance-based spectral indices to improve the models that use index-based products. It has been well demonstrated in the remote sensing literature that discrete-return LiDAR collected at high spatial resolution can accurately measure forest height, percent canopy cover, and provide three-dimensional canopy height and density metrics describing the vertical distribution of canopy material, aerodynamic roughness (Hudak et al., 2009; Lefsky et al., 2002; Smith et al., 2009), and gap size (Hudak et al., 2009; Kane et al., 2013). Analyzed in concert with field data, LiDAR returns can also be used to predict forest structure attributes such as basal area, volume, biomass, and leaf area (García et al., 2010; Hudak et al., 2009; Lefsky et al., 2002). LiDAR has been successfully used to quantify the effects of insect outbreaks in forests (Bater et al., 2010; Bright et al., 2012), pre-fire fuel loading (Andersen et al., 2005; García et al., 2011; Riaño et al., 2003, 2004; Seielstad and Queen, 2003), and structural measurements of the post-fire environment (Bishop et al., 2014; Kane et al., 2013, 2014; Kwak et al., 2010; Wulder et al., 2009). Structural datasets such as those derived from LiDAR data have been previously highlighted as holding considerable promise for directly quantifying changes in vegetation structure (Smith et al., 2014), but acquisitions of high-resolution, comparable pre- and post- fire LiDAR data that provide measure of fire-induced vegetation change have been limited (Bishop et al., 2014; Reddy et al., 2015; Wang and Glenn, 2009; Wulder et al., 2009). However, multi-temporal LiDAR is not a novel concept and has been widely applied to quantify other ecosystem properties such as snow volume (Tinkham et al., 2014), forest growth and harvest disturbance (Hudak et al., 2012), boreal forest gap dynamics (Vepakomma et al., 2008), and change in biomass resulting from a Gypsum moth (*Lymantria dispar)* outbreak (Skowronski et al., 2014), among other applications.

The comparison of structural changes in vegetation derived from multi-temporal LiDAR and spectral indices used to characterize burn severity is relatively novel. To-date, only two known studies have been able to spatially match pre- and post-fire LiDAR acquisitions in order to objectively quantify fire effects on forest structure (Bishop et al., 2014; Wulder et al., 2009), with additional studies by Wang and Glenn (2009) focused on shrubs in steppe ecosystems and Reddy et al. (2015) in peatlands. Neither of the prior studies in forest ecosystems explicitly linked LiDAR-derived forest structure metrics to the spectral indices that are most commonly used to assess forest burn severity across an entire fire; Bishop et al. (2014) assessed the Normalized Differenced Vegetation Index (NDVI) on a small portion of a wildfire, while Wulder et al. (2009) analyzed only a limited set of returns from a single LiDAR transect. There is an urgent need to contextualize unitless spectral indices that are widely-utilized to characterize burn severity and model emissions (e.g., dNBR and RdNBR) with specific environmental changes such as vegetative structure. Multi-temporal LiDAR presents arguably one of the best sources of contiguous forest structural data across large geographical areas, emphasizing the critical need for additional studies where pre- and post-fire LiDAR overlap.

One such opportunity arose following the 2012 Pole Creek Fire in Central Oregon, USA, where post-fire LiDAR was acquired spatially coincident with a pre-fire acquisition across an entire fire, featuring a gradient of forest types. Pre-fire LiDAR had been acquired in 2009 after mountain pine beetle (*Dendroctonus ponderosae*) caused extensive tree mortality throughout the upper elevation lodgepole pine stands approximately a decade before the fire (Agne et al., 2016; McCarley, 2016).