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Identification of the disturbance and trajectory types in mining areas using multitemporal remote sensing images

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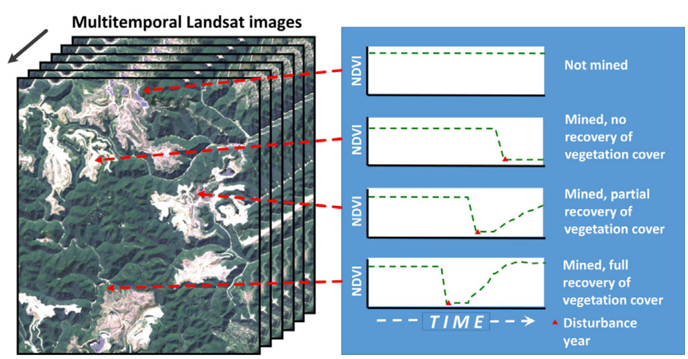
HIGHLIGHTS

- A method for analyzing Landsat data to identify mining disturbances is described.
- The method identifies where and when the mining disturbances occurred.
- The method characterizes recovery of vegetation cover after mining was completed.
- The method can be automated.
- The method provides results of high accuracy.

GRAPHICAL ABSTRACT



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ABSTRACT

Surface coal mining disturbances affect the local ecology, human populations and environmental quality. Thus, much public attention has been focused on mining issues and the need for monitoring of environmental disturbances in mining areas. An automated method for identifying mining disturbances, and for characterizing recovery of vegetative cover on disturbed areas using multitemporal Landsat imagery is described. The method analyzes normalized difference vegetation index (NDVI) data to identify sample points with multitemporal spectral characteristics ("trajectories") that indicate the presence of environmental disturbances caused by mining. A typical disturbance template of mining areas is created by analyzing NDVI trajectories of disturbed points and used to describe NDVI multitemporal patterns before, during, and following disturbances. The multitemporal sequences of disturbed sample points are dynamically matched with the typical disturbance template to obtain information including the disturbance year, trajectory type, and the nature of vegetation recovery. The method requires manual analysis of randomly selected sample points from within the study area to calculate several thresholds; once those thresholds are determined, the method's application can be automated. We applied the method to a stack of 26 Landsat images over a 32-year period, 1984 to 2015, for mining areas of Martin County KY and Logan County WV in eastern USA. When compared with the samples determined by direct interpretation, the method identified mining disturbances with 97% accuracy, the disturbance year with 90% accuracy, and disturbance-recovery trajectory type with 90% accuracy.

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1. Introduction

Remote sensing has become an effective tool for monitoring environmental changes (Coppin and Bauer, 1996; Mouat et al., 1993; Kaiser, 2009). Multispectral sensors mounted in satellites can record land-cover changes resulting from both natural and human disturbances at various spatial scales (Jin and Sader, 2006; Kwarteng and Chavez, 1998; Muchoney and Haack, 1994; Royle and Lathrop, 2002; Silapaswan et al., 2001; Wang and Sa, 2009; Yang et al., 2013; Pickell et al., 2014; Weng, 2001; Kennedy et al., 2007; Turner et al., 2003). Remote sensing has been applied successfully for land-cover change detection in many areas, and many methods for detecting change have been described (Kennedy et al., 2007). Multispectral remote-sensing images are becoming widely available and are often used for analysis and monitoring of environmental and land-cover change. MODIS imagery is widely used in land use/land cover change studies, but its relatively low spatial resolution (≥250 m) prevents its application to vegetation-change detection at small-to-medium spatial scale (Turner et al., 2003; Fuller et al., 2004; Wang et al., 2004; Leuning et al., 2005; Hansen et al., 2008). QuickBird, SPOT, and other imagery with higher spatial resolution can be more useful for small-to-medium scale change detection (Gopal and Woodcock, 1996; Xiao et al., 2002; Souza Jr. et al., 2003; Soudani et al., 2006; Chen et al., 2011), but the costs for purchasing the large numbers of images required for multitemporal studies can be large (Huang et al., 2015). In contrast, Landsat Thematic Mapper (TM), Enhanced Thematic Mapper (ETM+) and Operational Land Imager (OLI) images can be obtained for no cost, have 30-m spatial resolution, record surface reflectance and emission data for multiple spectral bands, and can serve as a suitable data source for land-cover change detection; Landsat imagery has been used successfully to identify disturbances in mining areas (Sen et al., 2012; Lutz et al., 2013; Li et al., 2015).

Over the past decade, methods for multitemporal analysis of remote sensing data for land-cover change detection have advanced rapidly. The available approaches range from trajectory-based analyses (Kennedy et al., 2007; Huang et al., 2010; Kennedy et al., 2010; Verbesselt et al., 2010a; Verbesselt et al., 2010b; Zhu et al., 2012; Verbesselt et al., 2013; Hermosilla et al., 2015) to classification-based analyses (Grinand et al., 2013; Griffiths et al., 2014). Temperate forest ecosystems during leaf-on growing seasons provide a relatively uniform spectral pattern through space and time, and thus, an ideal context for development and application of such methods. The concept of recovery, meaning spectral restoration to pre-disturbance conditions due to forest regrowth after harvest, is often utilized to aid identification of disturbance types in these studies (e.g. Kennedy et al., 2007; Huang et al., 2010). In recent years, time-series analyses were applied to characterize forest disturbance in several world regions, including Brazil (Lu et al., 2012), Australia (Lehmann et al., 2013), northeastern US (Jin and Sader, 2005), and Myanmar (Shimizu et al., 2017).

Many mineral sources are found in forest areas globally; mining in such areas causes the forest to be severely disturbed (World Resources Institute, 2014; Macdonald et al., 2015). Loss of forested ecosystems to various forms of land development is growing concern (FAO, 2015). Coal surface mining in Appalachia USA causes forest loss and severe alterations of landscapes; mining operations remove all vegetation and soil from the land surface, and also remove underlying geologic materials for the purpose of accessing underground coal seams. Although earth materials are replaced in mined areas following coal removal, the resulting landscape and soil differ in character from that which preceded mining; and, following mining, the natural forest vegetation is no longer present. We refer to mining activity as disturbance, given the severe alterations caused by mining to the land's natural state. As well as affecting the land surface and vegetation, mining disturbances also have indirect effects beyond the mined areas due to influence on water resources (Lindberg et al., 2011); aquatic ecology (Pond et al., 2014), terrestrial wildlife and ecosystems (Wickham et al., 2007; Wickham et al., 2013), and air quality and human health (Knuckles et al., 2013; Kurth et al., 2015; Boyles et al., 2017).

Mining in forested regions represents a specific type of forest disturbance, and researchers have adapted multitemporal analysis methods to identify mining disturbances in such areas. Essential to the identification of mined areas is the separation of mining from other forms for land disturbance. Sen et al. (2012) analyzed spectral trajectories for Normalized Difference Vegetation Index (NDVI) derived from Landsat images to define mining disturbances in an eastern US forested region; they separated mining from another common form of forest disturbance, urban development, by identifying spectral thresholds and rates of spectral recovery that are characteristic of mining disturbance. Li et al. (2015) advanced the Sen et al. (2012) method while also studying mining disturbance in the same region, also by employing sequential analyses of NDVI trajectories. They discriminated mined lands from unmined lands by defining a minimal forested NDVI, and analyzed Landsat data to reconstruct the disturbance history of mining area. According to Li et al. (2015), other disturbances such as developed sites and forest harvest account for a small proportion of the disturbed area within mine permit boundaries. Sen et al. (2012) and Li et al. (2015), however, did not characterize the recovery status of vegetation cover in mined areas in the years following disturbance.

The term "vegetation cover" refers to the fraction of the land surface that is covered by vegetation, and is expressed as a percentage or fraction. Laws such as Surface Mining Control and Reclamation Act (SMCRA) in USA and Land Reclamation Regulations in China, require that mined areas should be reclaimed by re-establishing vegetation; these laws place emphasis on re-establishing vegetation cover for purposes that include reducing mining impacts on soil erosion and water quality. Numerous studies have demonstrated that coverage of the land surface by vegetation also influences air-particle emissions (e.g. Stockton and Gillette, 1990; Ravi et al., 2010). So, it is very useful to detect mined areas' vegetative cover status and recovery through time, as well as when and where the mining disturbance occurred.

Here, we describe an automated method for identifying mining disturbances and classifying disturbance-recovery patterns. Our method identifies where and when mining disturbances occurred, like Sen et al. (2012) and Li et al. (2015); but also characterizes recovery of vegetation cover and its progression through time. In this manuscript, we provide detailed description of the method; we describe results of the method's application to a two-county study area in central Appalachian USA, and present accuracy assessment of those results; and we discuss the method's advantages and limitations.

2. Study area and data

2.1. Study area

The study area comprises Martin County and Logan County, which are located in the central part of the Appalachian coalfield in the United States (Fig. 1). Martin County is in the eastern part of Kentucky with a population of 12,929 in year 2010 and an area of 595 km^2 (https://www.census.gov/quickfacts/fact/table/martincountykentucky,US/PST045217). Logan County is located in the southwestern part of West Virginia with a population of 36,745 in year 2010 and an area of 1175 km^2 (https://www.census.gov/quickfacts/fact/table/logancountywestvirginia,US/PST045217). Both counties are predominantly mountainous areas with humid climates (annual rainfall >115 cm yr^{-1}; U.S. Climate Data 2017). Vegetation of both counties is dominated by forests with a small amount of grassland and farmland, some of which occurs on reclaimed coal mines. Both counties have long histories of surface coal mining. Surface mining methods of the central Appalachian coalfields include mountaintop removal, contour, area and highwall mining (EPA, 2016).