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Identifying optimal remotely-sensed variables for ecosystem monitoring in Colorado Plateau drylands

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ABSTRACT

Water-limited ecosystems often recover slowly following anthropogenic or natural disturbance. Multitemporal remote sensing can be used to monitor ecosystem recovery after disturbance; however, dryland vegetation cover can be challenging to accurately measure due to sparse cover and spectral confusion between soils and non-photosynthetic vegetation. With the goal of optimizing a monitoring approach for identifying both abrupt and gradual vegetation changes, we evaluated the ability of Landsat-derived spectral variables to characterize surface variability of vegetation cover and bare ground across a range of vegetation community types. Using three year composites of Landsat data, we modeled relationships between spectral information and field data collected at monitoring sites near Canyonlands National Park, UT. We also developed multiple regression models to assess improvement over single variables. We found that for all vegetation types, percent cover bare ground could be accurately modeled with single indices that included a combination of red and shortwave infrared bands, while near infrared-based vegetation indices like NDVI worked best for quantifying tree cover and total live vegetation cover in woodlands. We applied four models to characterize the spatial distribution of putative grassland ecological states across our study area, illustrating how this approach can be implemented to guide dryland ecosystem management.

1. Introduction

Drylands, which constitute about 40% of the Earth's terrestrial land mass, are defined as regions where the ratio of mean annual precipitation is less than two thirds of potential evapotranspiration, resulting in low overall soil moisture available to vegetation (Lal, 2004; Johnson et al., 2012; Yang et al., 2012). Dryland ecosystems often contain a large variety of endemic plant and animal species, and can support high biodiversity despite their high levels of aridity (Millennium Ecosystem Assessment, 2005; Stohlgren et al., 2005). Dryland ecosystems are strongly water-limited, and while many species are adapted to limited resources these ecosystems are vulnerable to falling into persistent degraded condition due to improper land-use, often coupled with abrupt climatic shifts (Weltzin et al., 2003; Lioubimtseva et al., 2005; Schwinning et al., 2008; Johnson et al., 2012). Understanding causes and patterns of persistent land degradation in responses to climate change and/or land-use in drylands, often referred to as “desertification” or “state change”, has become a focus of research and management in drylands globally in recent decades (Steele et al., 2012; Bestelmeyer et al., 2015).

The arid and semi-arid landscapes of the Colorado Plateau are highly susceptible to desertification due to climatic variations and human activities (Mouat et al., 1997; Dregne, 2002; Clements, 2004; Schwinning and Sala, 2004; Copeland et al., 2017; Munson et al., 2011a). Change-inducing drivers impacting Colorado Plateau drylands include current and historical overgrazing by cattle and sheep (Alzérreca-Angelo et al., 1998; Neff et al., 2005; Fernandez et al., 2008), the establishment and spread of invasive species (Evans et al., 2001; Stohlgren et al., 2001; Gelbard and Belnap, 2003), and the impacts of vegetation clearing associated with oil and gas development (Allred et al., 2015; Nauman et al., 2017). Deleterious ecosystem impacts of these activities include habitat fragmentation (Belnap, 2002; Copeland et al., 2009; Webb and Wilshire, 2012), soil erosion (Belnap and Gillette, 1998; Munson et al., 2011b), and increased dust production which has been shown to increase the rates of snowmelt in the Rocky Mountain snowpack (Painter et al., 2010; Deems et al., 2013;

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Skiles et al., 2015). Effective management of Colorado Plateau ecosystems requires information both on the extent and intensity of drivers of change, as well as spatiotemporal data on the distribution of ecosystem states (Steele et al., 2012) and ecosystem indicators that can be used to assess proximity or risk of an undesired state change (Bestelmeyer et al., 2013).

In the dryland ecosystems of the Colorado Plateau, indicators used to identify ecological states include cover and connectivity of bare ground, foliar cover of vascular plants, plant community composition, presence and abundance of invasive species, and cover of biological soil crusts (Herrick et al., 2005; Miller et al., 2011; Toevs et al., 2011; Duniway et al., 2016). Biological soil crusts (BSC), a thin layer of cyanobacteria, lichens and mosses, are particularly sensitive to surface disturbance (Weber et al., 2014). BSC play an important role in stabilizing dryland soils by protecting surfaces from wind and water erosion, and by limiting the amount of dust emitted into the air (Belnap and Gillette, 1998). Additionally, the presence of healthy BSC layers promotes viable water-holding capacity and fertility of soils by reinforcing the levels of plant-essential nutrients (Verrecchia et al., 1995; Belnap, 2003). The reduction of BSC cover from disturbance is a significant contributor to the desertification of arid regions due largely in part to the loss of soil stability and fertility as well as the increase of dust emissions. The effects of anthropogenic changes on vegetation, BSC and soils are often challenging to monitor over regional scales; the development of an accurate, flexible and repeatable methodology to reliably assess the effects of land change would benefit ecosystem monitoring, conservation and restoration efforts of dryland ecosystems.

Remote sensing provides a synoptic view of landscapes and has facilitated the monitoring of land change and recovery from disturbance (Mas, 1999; Weng, 2002; Wulder et al., 2009; Vogelmann et al., 2012; Bunting et al., 2017). Landsat Thematic Mapper (TM) data have been used to monitor the abundance and change in vegetation cover, often by calculating vegetation indices (VIs) that rely on differences in the red and near-infrared bands to capture the greenness of photosynthetic vegetation (PV) (Table 1; Tucker, 1979; Pickup, 1995; Dawelbait and Morari, 2008). However, dryland ecosystems are challenging to measure using remote sensing due to the frequent lack of a strong green vegetation signal, and confusion between non-photosynthetic vegetation (NPV) and spectrally variable bare ground that may include BSC (Smith et al., 1990; White et al., 2000; Dawelbait and Morari, 2008; Higginbottom and Symeonakis, 2014; Guerschman et al., 2015; Li and Guo, 2016). The Normalized Difference Vegetation Index (NDVI) has general utility for capturing quantities of green vegetation, but can be sensitive to soil background where soil fractions are high (Huete and Tucker, 1991). Various corrections to NDVI have been suggested to account for soil variability, particularly in drylands (e.g., SAVI; Table 1; Huete, 1988).

There are limits to accounting for spectral variability with a single index. Spectral mixture analysis (SMA; Smith et al., 1990) is an approach that can more explicitly account for soil background variability, by modeling each pixel as a mixture of spectral "endmembers" (e.g., green vegetation, soil, and shadow), and has been found to perform well in arid regions (Smith et al., 1990; Okin et al., 2001; Asner and Heidebrecht, 2002; Okin, 2007). Multiple endmember spectral mixture analysis (MESMA), in particular, may help to better quantify vegetation cover by optimizing the selection of spectral endmembers on a per-pixel basis (Roberts et al., 1998). This can help to account for soil variability and also better distinguish among contributions from photosynthetic vegetation, non-photosynthetic vegetation (NPV; Roberts et al., 1993) and soil.

Most of the power of MESMA comes from the application of large reference endmember libraries to hyperspectral image data (e.g., AVIRIS), which can be a drawback when considering regional monitoring applications. The use of lower dimensionality image data (i.e., Landsat) available for long time series analysis reduces the power of MESMA. Yet the handling of multiple dimensions of spectral information available with Landsat has substantial merit if easily implementable. For example, The Tasseled Cap approach (Table 1; Kauth and Thomas, 1976) easily incorporates the data dimensionality of Landsat and has proven popular for large area studies (Dymond et al., 2002; Zhang et al., 2002). Tasseled Cap Brightness, Greenness, and Wetness transforms are clearly related to SMA fractions of soil/shadow, green vegetation, and NPV, respectively, but may not be locally optimized.

A suite of variables that are locally optimized for spectral differences among PV, NPV, and bare soil, can be combined to form robust indicators of vegetation condition and gradual land change. Implementing the use of a suite of spectral variables to characterize vegetation states has proven to be useful in past studies (Hill, 2013; Wang et al., 2013; Villarreal et al., 2016a). A locally-optimized suite of remote sensing variables could supplement long-term, ground-based monitoring programs meant to track changes in vegetation and ecosystem condition (Jensen, 2000; Dawelbait and Morari, 2008; Duniway et al., 2012).

The objective of this study was to develop an easily implementable but robust remote sensing approach to monitor ecosystem indicators, with the goal of providing guidance for land managers interested in avoiding land degradation and promoting recovery in dryland ecosystems. To accomplish this we evaluated the ability of Landsat-derived spectral variables to characterize surface variability in vegetation cover and bare ground across a range of dryland vegetation community types. We used a mix of conventional spectral indices, band transformations and single reflectance bands that we hypothesized would capture the variability of PV, NPV and soil brightness present in dryland plant

Table 1
Landsat bands, spectral indices, and transformations selected for this study based on their known (and hypothesized) ability to capture three basic surface properties of drylands: photosynthetic vegetation (surface property = PV), non-photosynthetic vegetation (surface property = NPV), and bare ground (surface property = Soil).

Index	Acronym	Surface Property	Formula	Reference
Normalized Difference Vegetation Index	NDVI	PV	$\frac{(NIR-Red)}{(NIR+Red)}$	Tucker, 1979
Soil Adjusted Vegetation Index	SAVI	PV	$\frac{(NIR-Red)}{(NIR+Red+L)}(1+L)$	Huete, 1988
Tasseled Cap Transformation (greenness)	TCG	PV		Kauth and Thomas, 1976
Soil Adjusted Total Vegetation Index	SATVI	PV/NPV*	$\frac{(SWIR1-Red)}{(SWIR1+Red+L)}(1+L)-\frac{SWIR2}{2}$	Marsett et al., 2006
Non-Photosynthetic Vegetation Normalized Difference	NPVND	NPV	$\frac{SWIR1-(Red+NIR)}{SWIR1+(Red+NIR)}$	
Tasseled Cap Transformation (wetness)	TCW	NPV		Kauth and Thomas, 1976
Soil Normalized Difference Index	SNDI	Soil	$\frac{Red-(NIR+SWIR1)}{Red+(NIR+SWIR1)}$	
Tasseled Cap Transformation (brightness)	TCB	Soil		Kauth and Thomas, 1976
Landsat TM band 3 (0.63–0.69 μm)	Red	Soil		

L = soil brightness correction factor. *SATVI is considered a total vegetation index, and is therefore considered for both PV and NPV.