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Hyper-temporal remote sensing for digital soil mapping: Characterizing soil-vegetation response to climatic variability☆

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ABSTRACT

Indices derived from remotely-sensed imagery are commonly used to predict soil properties with digital soil mapping (DSM) techniques. The use of images from single dates or a small number of dates is most common for DSM; however, selection of the appropriate images is complicated by temporal variability in land surface spectral properties. We argue that hyper-temporal remote sensing (RS) (i.e., hundreds of images) can provide novel insights into soil spatial variability by quantifying the temporal response of land surface spectral properties. This temporal response provides a spectral 'fingerprint' of the soil-vegetation relationship which is directly related to a range of soil properties. To evaluate the hyper-temporal RS approach, this study first reviewed and synthesized, within the context of temporal variability, previous research that has used RS imagery for DSM. Results from this analysis support the notion that temporal variability in RS spectra, as driven by soil and climate feedbacks, is an important predictor of soil variability. To explicitly evaluate this idea and to demonstrate the utility of the hyper-temporal approach, we present a case study in a semiarid landscape of southeastern Arizona, USA. In this case study surface soil texture and coarse fragment classes were predicted using a 28 year time series of Landsat TM derived normalized difference vegetation index (NDVI) and modeled using support vector machine (SVM) classification, and results evaluated relative to more traditional RS approaches (e.g., mono-, bi-, and multi-temporal). Results from the case study show that SVM classification using hyper-temporal RS imagery was more effective in modeling both soil texture and coarse fragment classes relative to mono-, bi-, or multi-temporal RS, with classification accuracies of 67% and 62%, respectively. Short-term transitions between wet and dry periods (i.e., <6 months) were the dominant drivers of vegetation spectral variability and corresponded to the general timing of significant RS scenes within in our SVM models, confirming the importance of spectral variability in predicting soil texture and coarse fragment classes. Results from the case study demonstrate the efficacy of the hyper-temporal RS approach in predicting soil properties and highlights how hyper-temporal RS can improve current methods of soil mapping efforts through its ability to characterize subtle changes in RS spectra relating to variation in soil properties.

1. Introduction

Spectral indices derived from satellite imagery are important predictors used for digital soil mapping (DSM) (e.g., Boettinger et al., 2008; Grunwald, 2009; McBratney et al., 2003; Peng et al., 2015; Scull et al., 2003). DSM studies typically incorporate spectral indices from one or two image dates (or composites) into soil prediction models (i.e., mono- and bi-temporal), with far fewer instances of DSM models that incorporate multiple image dates (i.e., multi-temporal analysis). These trends are largely the result of: (i) historical barriers (e.g., financial, computational, analytical) that have prevented the use of high frequency imagery, and (ii) an underappreciation of the unique information encapsulated within the temporal response of land surface spectral properties. Recent technological and methodological advancements in the field of remote sensing (RS) are providing new opportunities for utilizing spectral indices derived from high frequency imagery stacks (e.g., MODIS, Landsat) for the modeling of soil properties and classes. Contrary to prior soil models that encapsulate a 'static' spectral view of the landscape (i.e., mono-temporal analysis), the use of hyper-temporal RS (i.e., hundreds of images) can uncover the temporal response of biophysical properties at the Earth's surface (e.g., vegetation), which in turn are linked in predictable ways to soil properties. In this paper we argue that hyper-temporal RS can provide novel insights into soil spatial

Abbreviations: κ, kappa statistic; PCC, percent correctly classified; PFT, plant functional type; RS, remote sensing; SVM, support vector machine.

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variability by quantifying the temporal response of each image pixel across a landscape.

Spectral indices provide information on soil properties and classes either directly through the imaging of bare soils (e.g., mineral indices, see Ben-Dor et al., 2008), or indirectly through the use of vegetation indices (e.g., NDVI) (Mulder et al., 2011). Given the predominance of vegetation across the Earth's land surface, a large portion of DSM efforts have incorporated vegetation indices into soil prediction models (Grunwald, 2009; Mulder et al., 2011). However, temporal variability in vegetation spectra resulting from seasonal changes in phenology and/or inter-annual soil-vegetation feedbacks to climate (e.g., El Nino-Southern Oscillation) can produce spurious results depending on the image date(s) chosen to derive vegetation indices. Consequently, previous studies using RS vegetation indices for DSM have employed two different methodologies to account for temporal variability. The first and most common methodology is to control for temporal variability by acquiring imagery that characterizes 'normal' conditions represented by an annual mean or multi-year mean composite image (Hengl et al., 2003; Page et al., 2013), or alternatively by a single image acquired during a specific time of year (e.g., annual peak biomass, dry season) (Chagas et al., 2013; Taghizadeh-Mehrjardi et al., 2015). The second and less common methodology is to characterize the temporal variability in vegetation spectra by utilizing bi-temporal (two images) or multi-temporal (three or more images) imagery, which can characterize differences in plant phenology, as well as changes driven by the soil-vegetation response to changes in climate.

While soil properties are largely static relative to vegetation, soils modulate the response of vegetation to climatic variability and in particular climatic extremes (i.e., physiological response to prolonged drought or elevated rainfall). Consequently, through quantifying temporal variability in land surface spectral properties (e.g., NDVI) we can gain greater insight into the spatial distribution of soil properties that regulate vegetation response (e.g., soil texture, water holding capacity, soil nutrient status). Changes in vegetative status occur on intra-annual time scales, reflecting increasing or decreasing plant vigor in response to available moisture. Alternatively, changes in fractional vegetation cover reflect an inter-annual response to prolonged periods of drought or abnormal wetness. From a remote sensing perspective, a single RS image provides a 'snapshot' of surface properties (e.g., variability in surface greenness relating to the distribution of plant functional types); however, areas identified as having similar spectral properties in a given image may experience vastly different temporal responses to variation in precipitation or temperature. Consequently, the accurate prediction of soil properties based on the soil-vegetation relationship and its response to climatic variability requires a measurement frequency that can adequately characterize these temporal dynamics. Thus, in contrast to bi-temporal and multi-temporal RS approaches which characterize seasonal and/or inter-annual variability at coarse temporal resolutions, hyper-temporal RS can characterize both intra- and inter-annual variability at a high temporal resolution, allowing the detection of subtle changes in RS spectra relating to soil variability. The temporal response of vegetation spectra derived from hyper-temporal RS provides a spectral 'fingerprint' of the soil-vegetation-climate relationship which is directly related to a range of soil properties. It should be recognized, however, that in highly managed ecosystems where the spectral signature of the landscape is artificially manipulated (e.g., agriculture), this approach will not likely produce reliable results unless those spectral changes can be accounted for (e.g., compiling all scenes across a time series when the area of interest is in corn production).

This study had two main objectives. The first objective was to review and synthesize, through the lens of temporal variability, previous research examining the use of RS imagery for DSM. The second main objective of this study was to test the utility of using hyper-temporal Landsat NDVI for predicting surface soil texture and coarse fragment classes in a semiarid landscape of southeastern Arizona, USA; and to evaluate these results relative to more traditional RS approaches (e.g., mono-, bi-, or multi-temporal).

2. Review and synthesis of RS applications for DSM: accounting for temporal variability

A wide range of RS data is now available for most regions of the world which presents many opportunities for predicting soil properties; hence, several reviews have been devoted to the use of RS in soil mapping (Grunwald et al., 2015; Mohanty, 2013; Mulder et al., 2011). A central premise in the estimation of soil properties using RS data is the existence of a predictable relationship between the spectral response measured by the sensor and the magnitude of the property of interest (Wulder et al., 2004). Several factors affect this relationship including the optical properties of the land surface (e.g., soil color, soil roughness, vegetation structure, leaf spectral properties); the effects caused by the spatial and temporal resolution of the sensor relative to the spatial structuring and temporal dynamics of the landscape; and finally environmental factors such as topography, sun elevation, and haze (Kerr and Ostrovsky, 2003). Consequently, the coupling of remote sensing and soil measurements has often produced mixed results due to the effects of the above stated factors, and in particular the inadequate accounting of temporal variability in RS spectra.

A summary of recent studies that have applied RS vegetation indices for soil property prediction is presented in Table S1. Our review of the literature was focused on how DSM studies account for and utilize temporal variability in RS spectra with a specific focus on the use of vegetation indices as covariates. DSM studies that utilize RS account for temporal variability in different ways and can be generally organized into four categories according to the number of images used: mono-temporal, bi-temporal, multi-temporal, and hyper-temporal.

Mono-temporal analysis, or the use of a single image, is the most common type of RS used for DSM. Mono-temporal analysis is most suited for properties that are temporally static, such as geology, parent material and other soil properties that can be identified by characterizing land surface color. For example, features like iron oxide, carbonate radicals, clay hydroxides, calcareous sediment, gypsiferous and natric soils are effectively identified with indices from multi-spectral RS (Bachofer et al., 2015; Boettinger et al., 2008; Nield et al., 2007). These types of applications require either adequate detection of the soil background (e.g., areas with minimal vegetation, periods of plant senescence) or the imaging of bare soils which requires the removal of all non-soil pixels (e.g., vegetation, water) prior to model development (Bachofer et al., 2015; Dutta et al., 2015; Nawar et al., 2015; Shabou et al., 2015). However, in many regions of the world the imaging of bare soils is not feasible due to extensive vegetation cover. As a result, many soil prediction models have applied vegetation indices (often in concert with other indices) derived from single image dates to predict a wide range of properties such as soil organic matter, salinity, phosphorus, physical soil properties and soil classes (Table S1). Since vegetation indices are temporally dynamic, the timing of imagery acquisition can strongly influence model development. To account for this, many studies have adopted the technique of aggregating multiple image dates to a single value (e.g., mean, maximum), which produces a representative, high quality image for a study area (Hengl et al., 2003; Kunkel et al., 2011; Page et al., 2013; Walker et al., 2003). For example, Page et al. (2013) produced an integrated NDVI representing the sum of both five and 10 year NDVI time series data to map soil carbon. Even though this approach utilizes multiple image dates, it does not exploit the temporal variability of image spectra within the model. While mono-temporal RS has been shown to be effective in predicting many soil properties, incorporating additional spectral variability (i.e., bi-temporal or multi-temporal RS) can improve model predictions for some soil properties (Blasch et al., 2015).

Bi-temporal RS, or the use of two images within a year or between years, is used to capture high magnitude changes in RS spectra/indices that may enhance soil prediction models (e.g., seasonal variation, soil moisture status). A common approach is to acquire imagery during both 'wet' and 'dry' conditions to capture phenological variation of