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Uncoupling the complexity of forest soil variation: Influence of terrain indices, spectral indices, and spatial variability

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ABSTRACT

Growing concern over climate and management induced changes to soil nutrient status has prompted interest in understanding the spatial distribution of forest soil properties. Recent advancements in remotely sensed geospatial technologies are providing an increasing array of data sources (e.g., LiDAR, hyperspectral imagery) relating to forest biophysical properties. While these data sources have the potential to improve spatial predictions of forest soil properties, considerable uncertainty exists regarding which remotely sensed (RS) indices are correlated to soil variability and what underlying pedogenic processes connect them. The main objective of this study was to identify and interpret RS indices that account for soil variability within a 2300 ha forested watershed. Redundancy analysis (RDA) and variation partitioning methods were used to uncouple the complexity of soil–environmental relationships. Thirty-two soil pedons were described, sampled, characterized and analyzed for 22 soil properties within the 0–50 cm soil depth interval. A suite of environmental covariates, comprised of LiDAR derived canopy metrics, land-surface and hydrologic terrain indices, broad-band remotely sensed indices (GeoEye-1), and narrow-band hyper-spectral indices (HyMap), were used as covariates in our RDA models. Principal coordinates of neighbor matrices (PCNM) was used to disentangle the contribution of spatial autocorrelation among sampling locations to the total variance explained by our RDA models. Two groups of soil properties were identified using discriminate analysis of principal components, with each soil property group (SPG) relating to different pedogenic processes occurring with the watershed (SPG1: organic matter-metal cycling; SPG2: base-cation cycling). Our results show there was a relatively strong correspondence between soil properties and terrain/spectral indices; with 61% and 81% of the total variance explained by the first four RDA axes for SPG1 and SPG2, respectively. Variation partitioning analysis revealed that both SPG1 and SPG2 were most strongly related to terrain and canopy indices; although spectral indices were also important, especially for SGP2. Variation in the types of RS indices correlated to each SPG results from variation in the degree to which each environmental covariate relates to the pedogenic process (es) driving soil property development. The approach used in this study can help improve our understanding of soil spatial variability through identifying the most significant environmental covariates related to soil variation. Given the growing demands placed upon forest ecosystems (e.g., timber, recreation, carbon sequestration), improved knowledge of soil variability and the factors that affect the soil resource is essential to facilitate more effective forest management.

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1. Introduction

Oregon's coastal mountain range supports some of the most productive forest ecosystems in the world (Spies et al., 1988). These high rates of primary productivity are largely due to a moderate, moist, maritime climate and highly fertile soils. Growing concern over climate and management induced changes to soil nutrient status has prompted interest in understanding the spatial distribution of forest soil properties and management classes

Abbreviations: RDA, redundancy analysis; SPG, soil property group; CCA, Canonical Correspondence Analysis; PCNM, principal coordinates of neighbor matrices; CEC, cation exchange capacity; BS, base saturation; ODOE, acid ammonium oxalate extract; TC, total carbon; TN, total nitrogen; DEM, digital elevation model; DAPC, discriminant analysis of principal components; BIC, Bayesian Information Criterion.

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(Binkley and Fisher, 2012; Peterman and Bachelet, 2012). Explicit knowledge of soil variability is important for implementing forest management practices that promote and maintain ecosystem productivity, defined as both market (e.g., harvestable timber) and non-market (e.g., soil carbon storage, fish and wildlife habitat, water) goods and services (Daily, 1995). The spatial distribution of forest soil properties across a landscape are significantly influenced by environmental factors such as topography, climate, parent material, and human disturbance (Jenny, 1941; McKenzie and Ryan, 1999). Among these factors, topography, climate, and parent material exert dominant controls on the genesis and morphology of soils in mountainous landscapes, thus directly influencing their spatial distribution. Elevation affects temperature and precipitation patterns, and slope and aspect affect soil moisture content (Butler et al., 1986; Daniels et al., 1987). Soil parent material influences weathering rates and availability of nutrients for vegetation, which in turn can affect the health and distribution of plant functional types (van Breemen et al., 1997).

The intrinsic relationships between soil properties and environmental variables form the basis for predictive soil modeling which requires an effective means of correlating soil properties to environmental attributes causal to soil variability. This has been the primary methodological approach taken for understanding soil genesis and distribution, as well as for the accurate prediction of soils at unknown locations. Remotely sensed (RS) terrain indices (e.g., elevation, slope, aspect) and spectral indices (e.g., enhanced vegetation index, moisture stress index) are two of the most common groups of environmental covariates used in digital soil mapping (Grunwald et al., 2011; Mulder et al., 2011; Scull et al., 2003). Local topography controls the way in which water and soil materials move through and over the land surface, as well as modifying the amount of surface solar radiation received, thus exerting significant control on soil development in high relief landscapes. Terrain indices have been used extensively to establish statistical associations with soil properties, including soil organic carbon (Arrouays et al., 1995; Gessler et al., 2000; Maynard and Johnson, 2014; McKenzie and Ryan, 1999; Miller et al., 2015; Moore et al., 1993; Ryan et al., 2000), texture (Arrouays et al., 1995; Bishop and Minasny, 2006; De Bruin and Stein, 1998; Levi and Rasmussen, 2014; Maynard and Johnson, 2014; McKenzie and Austin, 1993; Moore et al., 1993), and soil depth (GESSLER et al., 1995; McKenzie and Ryan, 1999; Park et al., 2001; Ryan et al., 2000; Sinowski and Auerswald, 1999; Walker et al., 1968). Similarly, spatial variations in spectral indices have been found to be linked to a range of soil properties (Mohanty, 2013; Mulder et al., 2011). For example, Normalized Difference Vegetation Index (NDVI) imagery has been related to root zone soil moisture (Wang et al., 2007), soil color (Singh et al., 2006), soil texture and water holding capacity (Lozano-Garcia et al., 1991), soil carbon and nitrogen content (Sumfleth and Duttmann, 2008), and soil management classes (Dobos et al., 2000).

Recent advancements in remote sensing technologies now provide a wide array of spatially contiguous covariates, at increasing levels of resolution (spatial, temporal, radiometric), that relate to forest biophysical properties. For example, the increasing availability of Light intensity detection and ranging (LiDAR) data has allowed the creation of high spatial resolution digital elevation models for deriving terrain indices (Maynard and Johnson, 2014), as well as spatially explicit quantification of forest canopy metrics (Gonzalez et al., 2010; Hansen et al., 2014). Forest canopy structure is a fundamental property of forest ecosystems that has been show to influence microclimate (Didham and Lawton, 1999), decomposition and nutrient cycling (Hobbie, 1992), and carbon storage (Asner et al., 2010). Additionally, hyper-spatial (e.g., Quickbird, GeoEye-1) and hyper-spectral (e.g., HyMAP) RS imagery have been found to correlate with forest structural (Gonzalez et al., 2010; Schlerf et al., 2005) and biochemical (Huang et al., 2004) attributes that may indirectly relate to forest soil properties. Given the increasing availability of these RS data sources, there is a need to explicitly evaluate which RS covariates explain soil variability.

We employed RDA and variation partitioning methods to uncouple the complexity of soil–environmental relationships between two sets of soil properties sampled from 32 pedons to a suite of RS derived variables (LiDAR derived terrain indices and canopy metrics, broad-band remotely sensed indices, and narrow-band hyper-spectral indices) in a 2300 ha mountainous forested watershed. Soil–environmental relationships were examined using data from the 0 to 50 cm soil depth interval. When conducting spatially explicit studies, additional complexity emerges from the potential spatial autocorrelation of soil sample locations. To account for the effects of spatial autocorrelation in our RDA models, we used principal coordinates of neighbor matrices (PCNM) eigenfunctions (Borcard and Legendre, 2002). PCNM eigenfunctions represent a decomposition of the spatial relationships among sampling locations. This method creates a set of explanatory variables (PCNMs: eigenvectors) that represent the spatial autocorrelation structure at all spatial scales within the dataset.

The specific objectives of this study were to: (i) quantify soil–environmental relationships in a forested watershed in Oregon's coastal mountain range, (ii) account for the spatial dependence of the predictor variables, and (iii) evaluate identified soil–environmental relationships in light of pedogenic processes and expert knowledge of soil development within the watershed.

2. Material and methods

2.1. Study site

The study was conducted in the Panther Creek Watershed, located on the east slope of the coastal mountain range of Oregon, USA (45°18′N, 123°21′W). The study area is approximately 2300 ha in size and is located in the upper reaches of the Panther Creek watershed (Fig. 1a). Elevations within the study area range from 100 to 700 m. The maritime climate is characterized by mild temperatures; a long frost-free season; prolonged cloudy periods; and heavy precipitation (Otte et al., 1974). Mean annual precipitation ranges from 200 to 250 cm at higher elevations (i.e., 400–700 m) resulting in a udic moisture regime, and 100–150 cm at lower elevations (i.e., 70–400 m) resulting in a xeric moisture regime, with 70% of precipitation occurring between November and March. Mean annual temperature in the study area is 12 °C, with the temperature regime ranging from frigid at higher elevations (400–700 m) to mesic at lower elevations (70–400 m). Vegetation within the watershed dominantly consists of planted stands of Douglas-fir, with significant amounts of western hemlock, western red cedar, grand fir, red alder, and big leaf maple (Hoffert-Hay, 2001). The study area is actively managed for timber production with an average rotation cycle of 40–60 years, resulting in a patchwork of even-aged Douglas-fir stands ranging from recent clearcuts to mature second-growth forests (Fig. 1b). Within the watershed, land holdings are split between private (54%) and public (46%) ownership resulting in a range of different land-use practices and long-term management goals (Creutzburg et al., 2015).

2.2. Soil sampling and analysis

The soils of this region are derived from basaltic diabase at higher elevations and a mix of diabase and deep-water marine siltstone/sandstone (Yamhill Formation) at lower elevations. Soils forming on smooth steep slopes tend to be shallow, with stony-loam textures, whereas soils forming on uneven or unstable slopes