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Distribution of near-surface permafrost in Alaska: Estimates of present and future conditions

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ABSTRACT

High-latitude regions are experiencing rapid and extensive changes in ecosystem composition and function as the result of increases in average air temperature. Increasing air temperatures have led to widespread thawing and degradation of permafrost, which in turn has affected ecosystems, socioeconomics, and the carbon cycle of high latitudes. Here we overcome complex interactions among surface and subsurface conditions to map near-surface permafrost through decision and regression tree approaches that statistically and spatially extend field observations using remotely sensed imagery, climatic data, and thematic maps of a wide range of surface and subsurface biophysical characteristics. The data fusion approach generated medium-resolution (30-m pixels) maps of near-surface (within 1 m) permafrost, active-layer thickness, and associated uncertainty estimates throughout mainland Alaska. Our calibrated models (overall test accuracy of ~85%) were used to quantify changes in permafrost distribution under varying future climate scenarios assuming no other changes in biophysical factors. Models indicate that near-surface permafrost underlies 38% of mainland Alaska and that near-surface permafrost will disappear on 16 to 24% of the landscape by the end of the 21st Century. Simulations suggest that near-surface permafrost degradation is more probable in central regions of Alaska than more northerly regions. Taken together, these results have obvious implications for potential remobilization of frozen soil carbon pools under warmer temperatures. Additionally, warmer and drier conditions may increase fire activity and severity, which may exacerbate rates of permafrost thaw and carbon remobilization relative to climate alone. The mapping of permafrost distribution across Alaska is important for land-use planning, environmental assessments, and a wide-array of geophysical studies.

1. Introduction

Climate change has led to an increase in high-latitude air temperatures that are nearly double that of the global average (Intergovernmental Panel on Climate Change (IPCC), 2007). This increase in air temperature has led to widespread thawing and degradation of permafrost (Jorgenson, Racine, Walters, & Osterkamp, 2001; Jorgenson, Shur, & Pullman, 2006), which has associated impacts on ecosystems, socioeconomics, and the carbon cycle of high latitudes. Climate warming is projected to continue in the Northern Hemisphere through the 21st Century (IPCC, 2013), where permafrost is currently estimated to underlay approximately 22% of the land surface (Brown, Ferrians, Heginbottom, & Melnikov, 1997). Further warming could cause ground temperature increases, a thickening of the active layer, talik formation, changes in hydrology and topography, remobilization of carbon pools, coastal erosion, and damages to infrastructure (Chapin et al., 2000; Grosse et al., 2011; Jorgenson et al., 2010, 2013; Larsen et al., 2008; Osterkamp et al., 2009; Walvoord & Striegl, 2007). Despite permafrost's influence on ecosystem structure and functions, relatively little has been done to quantify permafrost properties across large areas and in great detail. While generalized and small-scale maps of permafrost properties exist (e.g. Brown et al., 1997; Jorgenson, Yoshikawa, et al., 2008), these map products do not account for important and local factors that influence permafrost systems. The development of spatially detailed information

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of permafrost properties is important because it can serve as an input into models predicting permafrost change. Thus, additional data and integrative approaches are needed to adequately observe and monitor permafrost (National Research Council, 2014).

Detection and monitoring of permafrost is difficult, however, because it is a subsurface condition of the ground, heterogeneous in nature, and largely found in remote locations (Riseborough, Shiklomanov, Etzelmüller, Gruber, & Marchenko, 2008). Spatial modeling of permafrost properties have largely been conducted at coarse-scale resolutions (>2 km × 2 km) (e.g. Brown et al., 1997; Jafarov, Marchenko, & Romanovsky, 2012; Lawrence & Slater, 2005; Marchenko, Romanovsky, & Tipenko, 2008), which do not represent fine-scale differences in permafrost conditions and are unsuitable for land-use planning and environmental assessments (Zhang, Olthof, Fraser, & Wolfe, 2014). Furthermore, accuracy assessments conducted at coarse scales can be unreliable because of differences in scale between maps and field observations, and assessments tend to lack a diverse set of field observations for thorough validation and calibration. More recently, several studies have applied process-based or transient models to improve representation of permafrost properties and dynamics at high resolutions (Panda, Marchenko, & Romanovsky, 2014a,b; Zhang, 2013; Zhang et al., 2012, 2014) for relatively small areas (i.e. <25, 000 km^2) in Alaska and Canada. However, because of high computational needs and the lack of detailed soils data needed for process-based or transient simulations, these approaches are currently impractical for mapping permafrost across extremely large areas. Statistical-empirical models have also been successfully applied to larger areas by quantifying relations between permafrost properties and ecological factors influencing the distribution of permafrost (Bonnaventure, Lewkowicz, Kremer, & Sawada, 2012; Mishra & Riley, 2014; Pastick, Jorgenson, et al., 2014). These automated approaches have been replacing the traditional photo-interpreted, terrain-unit approach based on landform-soil associations (Jorgenson, Yoshikawa, et al., 2008; Jorgenson et al., 2014; Kreig & Reger, 1982). Statistical-empirical models are particularly robust when a diverse set of high-quality field and geospatial data are available, as demonstrated in this study.

We overcome complexities inherent in permafrost mapping through decision and regression tree modeling approaches that statistically and spatially extend field observations using remotely sensed imagery, climatic data, and thematic maps of a wide range of surface and subsurface biophysical characteristics. This novel study expands upon decades of permafrost-related research by producing the first medium-resolution (30 m × 30 m) maps of near-surface (within 1 m) permafrost (NSP), active-layer thickness (ALT: depth to surface of permafrost), and associated uncertainty estimates, throughout all of mainland Alaska. Calibrated models were then used to quantify changes in permafrost extents under varying climate scenarios while holding other biophysical factors constant. Recently created soil carbon maps and simulated changes in near-surface permafrost extent were then used to quantify frozen C pools that are potentially liable to remobilization upon thaw. Ecological factors influencing the distribution of NSP are also examined and discussed. The work presented here provides a detailed depiction of the distribution of permafrost properties in Alaska (excluding the Aleutian and Bering Sea Islands), which is important for land-use planning, environmental assessments, and a wide-array of geophysical studies.

2. Methods

2.1. Study area and field observations

Alaska (~1,500,000 km^2) is composed of a diverse set of ecosystems, and 80% of the land surface is estimated to be within permafrost zones (Jorgenson, Yoshikawa, et al., 2008). Within this study, approximately 17,000 field measurements were used to represent permafrost properties across Alaska. These field observations were obtained from various soil databases and researchers, with the majority of the dataset coming from the Natural Resource Conservation Service (Clark & Duffy, 2003), ABR, Inc. (Jorgenson et al., 1999; Jorgenson, Racine, et al., 2001; Jorgenson, Roth, et al., 2001; Jorgenson, Yoshikawa, et al., 2008), and the U.S. Geological Survey and U.S. Fish and Wildlife Service (Pastick et al., 2013; Pastick, Jorgenson, et al., 2014). Field measurements of ALT and the presence–absence of NSP were collected from 1990 to 2013. To circumvent the use of seasonal frost observations, only thaw-depth measurements taken during late-season months (late July to mid-September) or measurements designated to have no NSP were used for model calibration and validation. Annual and slight seasonal variations in active layer thickness and corresponding field measurements could introduce bias within our model estimates. While temporal variability among field observations may be of some concern for ALT estimations, it is less likely to be of concern for estimations of the presence–absence of NSP because the presence–absence of permafrost is designated at a fixed depth interval and a smaller portion of the field observations would be affected by temporal variations in thaw depths. Areas classified as open water, cultivated, perennial ice/snow, bare soil, or developed areas, by the National Land Cover Database (Homer et al., 2007), were masked out in this study, as these areas are typically devoid or underlain by NSP. For instance, limited NSP field observations coinciding with areas mapped as water ($n = 243$), perennial ice/snow ($n = 8$), bare soil ($n = 235$), developed ($n = 51$), and cultivated areas ($n = 33$) held mean NSP probabilities/frequencies of 28%, 88%, 21%, 25%, and 9%, respectively.

Though the field observations were unevenly distributed across Alaska (Fig. 1), the samples represent all major ecoregions (Nowacki, Spencer, Brock, Fleming, & Jorgenson, 2001), land cover types, and surficial deposits and soil textures (Jorgenson, Yoshikawa, et al., 2008). Field observations of the presence–absence of NSP ($n = 16,786$; Present = 4322; Absent = 12,464) followed temperature gradients as expected, with more observations of the presence of NSP in colder regions and more observations of the absence of NSP in warmer regions of Alaska. The mean, median, standard deviation, and coefficient of determination, of those NSP measurements where the ALT was fully resolved (Fig. 2; $n = 4834$), were 58 cm, 49 cm, 32 cm, and 54%, respectively. Field observations were also used to assess environmental factors influencing the distribution of NSP, as discussed below.

2.2. Environmental predictors

Geospatial datasets served as environmental predictors in our permafrost models and as a continuous estimation surface to which we could apply predictive models. For the purposes of this study, environmental predictors were resampled to a 30-m spatial resolution to better match the scale of our field observations and the spectral information used in this study. Environmental predictor information was then extracted to each point observation, compiled into a modeling database, and incorporated into variable selection analyses. We explored the utility of a large number of geospatial datasets, which can help depict various surface and subsurface conditions, because permafrost responds to a wide range of ecological factors and is covered by surface vegetation and soil within the active layer.

2.2.1. Topography

Regional topographic effects can influence permafrost properties where permafrost conditions may vary with changes in elevation, slope, and aspect (Peddle & Franklin, 1993). A downscaled 30-m resolution digital elevation model (Gesch et al., 2002) and derived terrain attributes (i.e. slope, aspect, potential incident radiation, and a compound topographic index) were incorporated into our analyses, as these attributes can serve as proxies for soil moisture and run-off, and incident radiation. The compound topographic index is a steady-state wetness index (Gessler, Moore, McKenzie, & Ryan, 1995) and a function of both slope and flow direction. Potential incident radiation was calculated