Predicted active-layer (AL) thicknesses of permafrost-affected soils influence earth system model predictions of C-climate feedbacks; yet, only a few observation-based studies have estimated AL thicknesses across large regions and at the spatial scale at which they vary. We used spatially referenced soil profile description data \((n = 153)\) and environmental variables (topography, climate, and land cover) in a geographically weighted regression approach to predict the spatial variability of AL thickness across Alaska at a 60-m spatial resolution. The predicted AL thickness across Alaska ranged from 0.14 to 0.93 m, with a spatial average of 0.46 m and a coefficient of variation of 30%. The average prediction error and ratio of performance to deviation were 0.11 m and 1.8, respectively. Our study showed mean annual surface air temperature, land cover type, and slope gradient were primary controllers of AL thickness spatial variability. We compared our estimates with Coupled Model Intercomparison Project Phase 5 (CMIP5) earth system model predictions; those predictions showed large interquartile ranges in predicted AL thicknesses \((0.35–4.4 \text{ m})\) indicating substantial overestimate of current AL thickness in Alaska, which might result in higher positive permafrost C feedback under future warming scenarios. The CMIP5 predictions of AL thicknesses spatial heterogeneity were unrealistic when compared with observations, and prediction errors were several times larger in comparison to errors from our observation-based approach. The coefficient of variability of AL thickness was substantially lower in CMIP5 predictions compared to our estimates when gridded at similar spatial resolutions. These results indicate the need for better process representations and representation of natural spatial heterogeneity due to local environment (topography, vegetation, and soil properties) in earth system models to generate a realistic variation of regional scale AL thickness, which could reduce the existing uncertainty in predicting permafrost C-climate feedbacks.

**Abbreviations:** AL, active-layer; CALM, Circumpolar Active Layer Monitoring Network; CMIP5, Coupled Model Intercomparison Project Phase 5; ESM, earth system models; GWR, geographically weighted regression; IPCC, Intergovernmental Panel on Climate Change; MEE, mean estimation error; NLCD, National Land Cover Database; RPD, ratio of performance to deviation.
potential thawing of permafrost C makes these regions a vulnerable component of the global C cycle (McGuire et al., 2009; Schuur et al., 2008; Schuur and Abbott, 2011), with the potential for large positive feedbacks with the atmosphere.

Within a soil profile underlain by permafrost (the portion of the soil profile where temperatures have remained at or below 0°C for at least two consecutive years), the AL is the top portion of the soil column that freezes in winter and thaws in summer (Zhang et al., 2005). The AL thickness or depth is measured as the maximum depth of thaw in any particular year. The spatial variability of current AL thickness is a critical component in prediction of the C-climate feedbacks associated with permafrost-affected soils (Nelson et al., 1998; Zhang et al., 2012).

Ground temperature observations from Alaska over the last 30 yr have indicated an increase in permafrost temperatures of 0.5 to 3°C (Osterkamp, 2005). These temperature increases have been linked to increased AL thickness and decreased permafrost extent (Zhang et al., 2005; Jorgenson et al., 2010). The large increases in temperature (3.2–3.5°C) predicted by 2100 in high-latitude regions (IPCC, 2007) could deepen AL thickness, thereby decreasing permafrost thickness and moving soil organic C into the AL, making it more susceptible to microbial decomposition and erosion. Despite recent advances in land-surface models, accurate predictions of AL thicknesses at regional and circumpolar scales remain a major scientific challenge (Riseborough et al., 2008).

Previous observation-based studies have reported AL thickness at several sites in Alaska. At 21 sites in the Arctic Coastal Plain and Arctic Foothills of Alaska, AL thickness ranged from 30 to 90 cm (Bockheim, 2007). In an observation-based spatial modeling study, Nelson et al. (1997) showed variability of AL thickness to range from 0 to more than 70 cm in a heterogeneous landscape in the Kuparuk region of north central Alaska. Hinkel and Nelson (2003) showed spatial patterns of average (1995–2000) AL thickness ranging from 20 to 120 cm at seven circumpolar monitoring sites in northern Alaska. These studies reported varying environmental controls of AL thickness depending on spatial scale. For example, at the landscape scale, AL thickness was strongly correlated with mean annual air temperature. At the local scale, topographic attributes, vegetation types, and soil properties were primary controllers of AL thickness. We note that different controls across scales may emerge when considering processes important to climate change prediction, e.g., C and nutrient cycling, which will also be impacted by other processes (e.g., moisture, vegetation) with their own spatial scaling properties (Crow et al., 2012).

Recent process-based and earth system modeling studies (Lawrence and Slater, 2005; Marchenko et al., 2008; Schaefer et al., 2011; Koven et al., 2011; Koven et al., 2013) have predicted spatial variability of AL thickness across Alaska and the Northern Hemisphere at coarse spatial resolutions (>100 km). The modeled AL thicknesses from earth system models (ESMs) influence the predicted C-climate feedbacks at a global scale. Among different ESMs, the Coupled (i.e., interactive two-way coupling between the land and atmosphere) Model Intercomparison Project phase 5 (CMIP5) model simulation experiments used state-of-the-art ESMs that incorporate mechanistic descriptions of the soil and surface energy balance and C cycle dynamics to study global C-climate feedbacks (Taylor et al., 2009). The purpose of these experiments was to address scientific questions that arose as part of the Intergovernmental Panel on Climate Change (IPCC) fourth assessment report, improve understanding of climate, and provide estimates of future climate change that could be used by climate change adaptation policies (Taylor et al., 2009). The results from these CMIP5 models are being used in the current IPCC fifth assessment report. Though these models predict general patterns of permafrost distribution and their responses to climate change, they are difficult to use for land-use planning and management and for ecological monitoring and assessment (Zhang et al., 2012) because they are unable to represent the fine-scale spatial heterogeneity in climate (e.g., temperature, moisture) and environmental parameters (e.g., topography, vegetation, soil, and hydrologic conditions) reported to affect AL thickness (Nelson et al., 1998; Riseborough et al., 2008).

Thus, tracking subgrid heterogeneity (e.g., in topography) over regional scales, such that the predicted AL depths reflect the heterogeneous controls of environmental variables, remains a critical scientific challenge (Riseborough et al., 2008). To evaluate land model predictions of current and future high-latitude C exchanges with the atmosphere, we believe there is a need for observationally constrained characterizations of AL at spatial scales consistent with existing heterogeneity. To that end, we developed finely resolved observation-based estimates of the spatial variability of AL thicknesses across Alaska and linked these values to climate and environmental controllers. Finally, we compared our results with other observation-based studies, several uncoupled (i.e., not prognostically coupled to an atmospheric model) land model predictions, and eight CMIP5 ESM predictions (Table 1).

**MATERIALS AND METHODS**

**Study Area and Soil Profile Observations**

This study was conducted in Alaska, which covers a land area (excluding ice, water, and bare rocks) of 1,221,272 km². A total of 153 georeferenced permafrost soil profile observations were collected from a recently published database (Michaelson et al., 2013). This database updated all the existing pedon observations from Alaska and contains observations collected from the University of Alaska Fairbanks northern soils research program and USDA-NRCS. In this database, the AL thickness of 59 samples were directly measured by digging soil profiles and measuring the depth to the permanently frozen portion of the soil profile, and in the remaining 94 samples AL thickness was calculated as depth to soil horizons with permanently frozen layers as indicated by the “f” suffix, such as Cf, Cgf, and Bgf (Soil Survey Staff, 2010; Mishra and Riley, 2012; Ping et al., 2013) of the soil profile. Both model calibration and validation data are sparsely and unequally distributed across Alaska (Fig. 1a) pri-
marily due to logistical difficulties and extreme working conditions of permafrost terrain.

Environmental Datasets

We used a digital elevation model of 60-m spatial resolution from the USGS database (Multi-Resolution Land Characteristics Consortium, 2011). The elevation of the study area ranged from sea level to 6188 m. High-elevation areas are located in the southeastern part of Alaska, and low-elevation areas are located in the western and northern parts of Alaska. We derived several primary and secondary topographic attributes to evaluate their use in predicting AL thickness. These topographic attributes included elevation, slope, aspect, curvature (plan, profile, and total), upslope contributing area, flow length, soil wetness index, sediment transport index, stream power index, terrain characterization index, and slope aspect index (Thompson et al., 2006). Land cover data of 60-m spatial resolution were extracted for Alaska from the National Land Cover Database (NLCD; Multi-Resolution Land Characteristics Consortium, 2011). We reclassified the NLCD land cover types into nine major categories (Table 2). The largest land area was under the scrub (shrub less than 5 m tall) category (43%), followed by forest (25%), barren (8.5%), herbaceous (7%), and wetlands (7%). The remaining surface area (9.5%) was under open water, perennial ice, barren, cultivated, and developed categories. For climate data, we used the 30-yr (1961–1990) mean annual air temperature and annual precipitation from the PRISM database (Daly et al., 2000). Across Alaska, the mean annual air temperature and mean annual precipitation ranged from −18 to 6°C and 150 to 8500 mm, respectively. Indicator variables for the presence or absence of land cover types were created and used in the model selection process. Climate datasets that were available at 2 km spatial resolution were resampled to a common spatial resolution of 60 m by using the resample function of ArcGIS (ArcGIS version 10, Environmental Systems Research Institute, Inc., Redlands, CA).

Spatial Modeling, Environmental Controls, and Comparison with Coupled Model Intercomparison Project Phase 5 Predictions

We used a geographically weighted regression (GWR) approach (Mishra and Riley 2012) to predict the AL thickness across Alaska. First, the best subset regression was used to identify the environmental variables that could be used in further modeling steps (Table 3 and 4). We used a Mallow’s $C_p$ criterion for model selection (Kutner et al., 2004). In Mallow’s $C_p$ criterion, a subset of predictors were identified for which $C_p$ value was small (small total mean squared error) and nearly equal to the number of predictors (small bias of the regression model). Among the environmental variables considered in this study, only slope, temperature, and land cover type were significant predictors of AL thickness across Alaska ($Mallow’s C_p = 3.4$). Selected independent variables were tested for unequal error variance, multicollinearity of variables, normality, and randomness of residuals. The SAS statistical software (SAS Institute, 2004) was used for this purpose. Selected independent variables were then used in a GWR approach, and the model parameters were derived at a 1000-m regular interval throughout the study area. The calibration $R^2$ ranged from 0.15 to 0.65 in the study area.

Table 1. Eight Coupled Model Intercomparison Project Phase 5 (CMIP5) model outputs used for active-layer thickness comparison across Alaska.

<table>
<thead>
<tr>
<th>Models</th>
<th>Modeling groups</th>
<th>References</th>
</tr>
</thead>
<tbody>
<tr>
<td>BCC-CSM1-1</td>
<td>Beijing Climate Center</td>
<td>Ji, 1995</td>
</tr>
<tr>
<td>CanESM2</td>
<td>Canadian Earth System Model</td>
<td>Verseghy, 1991</td>
</tr>
<tr>
<td>GFDL-ESM2G</td>
<td>Geophysical Fluid Dynamics Laboratory</td>
<td>Dunne et al., 2012</td>
</tr>
<tr>
<td>GISS-E2-R</td>
<td>Goddard Institute for Space Studies</td>
<td>Rosenzweig and Abramopoulos, 1997</td>
</tr>
<tr>
<td>HadCM3</td>
<td>Hadley Center Coupled Model</td>
<td>Cox et al., 1999</td>
</tr>
<tr>
<td>HadGEM2-CC</td>
<td>Hadley Center Global Environmental model</td>
<td>Essery et al., 2003</td>
</tr>
<tr>
<td>HadGEM2-ES</td>
<td>Hadley Center Global Environmental model</td>
<td>Essery et al., 2003</td>
</tr>
<tr>
<td>MPI-ESM-LR</td>
<td>Max Plank Institute Earth System Model</td>
<td>Raddatz et al., 2007</td>
</tr>
</tbody>
</table>

Fig. 1. Distribution of observations (a) and predicted active-layer thickness using geographically weighted regression across Alaska (b). Black color indicates surface area without permafrost based on Brown et al. (1998). CALM, Circumpolar Active Layer Monitoring Network.
Table 2. Reclassification of USGS land cover types for this study.

<table>
<thead>
<tr>
<th>National Land Cover Database land cover type</th>
<th>Reclassified land cover type</th>
</tr>
</thead>
<tbody>
<tr>
<td>Developed open space, low intensity, medium</td>
<td>Developed</td>
</tr>
<tr>
<td>intensity, and high intensity</td>
<td></td>
</tr>
<tr>
<td>Deciduous, evergreen, and mixed forest</td>
<td>Forest</td>
</tr>
<tr>
<td>Dwarf scrub and shrub scrub</td>
<td>Scrub</td>
</tr>
<tr>
<td>Shrub, sedge, and moss</td>
<td>Herbaceous</td>
</tr>
<tr>
<td>Pasture and cultivated lands</td>
<td>Cultivated</td>
</tr>
<tr>
<td>Woody and herbaceous wetlands</td>
<td>Wetland</td>
</tr>
<tr>
<td>Barren</td>
<td>Barren</td>
</tr>
<tr>
<td>Open water</td>
<td>Open water</td>
</tr>
<tr>
<td>Perennial ice</td>
<td>Perennial ice</td>
</tr>
</tbody>
</table>

area. In GWR, the weight function was chosen as an adaptive spatial kernel type so that the spatial extent for included samples varied based on sample density (Fotheringham et al., 2002). The GWR approach used in this study can be represented as

\[ D_i = \beta_0(u_i, v_i) + \beta_1(u_i, v_i)X_{1i} + \beta_2(u_i, v_i)X_{12} + \cdots + \beta_k(u_i, v_i)X_{ik} \]

where \( D_i \) is the predicted AL thickness (m) at location \( i \); \( (u_i, v_i) \) are the coordinates for location \( i \); \( \beta_0 \) to \( \beta_k \) are regression coefficients; \( X_{1i} \) to \( X_{ik} \) are environmental variables at location \( i \); and \( k \) is the number of environmental variables. The GWR model parameters used in this study are provided in Table 4.

The prediction accuracy of the resulting AL thickness maps (both from our approach and ESMs) was evaluated using data from 34 locations across Alaska from the circumpolar active-layer monitoring network (CALM, 2013) (Brown et al., 2000); these data were not included in the development of our GWR model and so allow for an independent check on our predictions.

GWR model predicted values of AL thicknesses were extracted for these locations. The observed values from the Circumpolar Active Layer Monitoring Network (CALM) dataset and predicted values from our approach and ESMs (CMIP5 coupled simulations) were interpreted by calculating mean estimation error (MEE) and RMSE:

\[ \text{MEE} = \frac{1}{n} \sum_{i=1}^{n} (D(x_i) - \hat{D}(x_i)) \]

\[ \text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (D(x_i) - \hat{D}(x_i))^2} \]

where \( D(x_i) \) is the CALM-measured AL thickness, \( \hat{D}(x_i) \) is the predicted AL thickness (both from our approach and ESMs), and \( n \) is the number of validated observations (Mishra et al., 2012). Both MEE and RMSE values should approach zero for an optimal prediction. We calculated the ratio of performance to deviation (RPD, defined as the ratio between the standard deviation and the RMSE), which indicates the overall prediction ability of the selected approach (Chang and Laird, 2002). A higher RPD value indicates greater accuracy in prediction.

Environmental controls on observation-based AL thickness predictions were examined by converting temperature and slope gradient data into different zones (creating zones of 4°C, and 10° slope) and then calculating the statistical parameters, such as average and standard errors of AL thickness in each zone. Similar calculations were performed for impacts of land cover types on AL thickness variability.

We also compared our models’ representation of current AL thickness distribution across Alaska with predictions from offline models and eight coupled ESMs that contributed to the CMIP5 database (Taylor et al., 2009). Active-layer thicknesses (thaw depth) in CMIP5 models were calculated using monthly mean soil temperatures from the depth resolved ESM grid cells. Monthly mean thaw depth was calculated as the deepest point in the soil column of a given grid cell at a given month by defining the freezing point as 0°C. Annual AL thickness was then calculated as the maximum monthly thaw depth for a given year. Detailed description of this calculation is provided in Koven et al. (2013).

From the eighteen CMIP5 models that reported sufficient soil temperature predictions to infer AL thickness, we selected the top eight of the models based on the closest median AL thickness predictions compared to our GWR prediction estimates in predicting AL thickness across Alaska: Beijing Climate Center Climate System Model version 1-1 (BCC-CSM1-1), Canadian Earth System Model version 2 (CanESM2), Geophysical Fluid Dynamics Laboratory Earth System Model with GOLD Ocean Component (GFDL-ESM2G), Goddard Institute for Space Studies model E coupled with Rusell Ocean Model (GISS-E2-R), Hadley Center coupled model version 3 (HadCM3), Hadley Center Global Environmental Model version 2 C Cycle (HadGEM2-CC), Hadley Center Global Environmental Model version 2 Earth System (HadGEM2-ES), and Max Plank Institute Earth System Model Low Resolution (MPI-ESM-LR). For comparison between our observation-based and the CMIP5 predictions, we used median and interquartile range of AL thicknesses predicted in different models and calculated MEE, RMSE, and RPD using the CALM validation dataset. We also compared the CVs of AL thickness in selected models with CVs of our predictions by gridding them at the same spatial resolutions.
RESULTS AND DISCUSSION

Descriptive Statistics of Observed Data

Across the observations from the 153 permafrost pedons, observed AL thicknesses showed a large range with positively skewed distribution (coefficient of skewness = 1.2). The average AL thickness for all of Alaska was 0.49 m, ranging from 0.16 to 1.27 m, with a high spatial variability (CV = 62%). In cases where the study area is large and observations are distantly located, such as ours, the mean value of the same variable could be different in different locations. In such cases CV is useful for assessing the spatial variability of investigated variable (Webster and Oliver, 2007). The median AL thickness and the standard deviation were 0.45 m and 0.20 m, respectively. Consistent with expectations, the observations indicated deeper AL thickness in the southern part of Alaska and shallower AL thickness in the northern parts of Alaska.

Spatial Variability of Observation-Based Active-Layer Thickness Predictions

Using the GWR spatial prediction approach described above, we predicted the average AL thickness for Alaska to be 0.46 m (range of 0.14–0.93 m). The average AL thickness increased from north to south; the lowest values were in the arctic coastal plains, and the highest values were in the subarctic coastal plains and lowlands of the Bering Taiga ecoregion (Fig. 1b). On average our approach under predicts the AL thickness by 3.6 cm (MEE = −3.6 cm). The average error (RMSE) of AL thickness prediction compared to the CALM observations was 0.11 m (25% of mean value), and the observed RPD was 1.8. These global validation indices showed good prediction accuracy for AL thickness across the state (Chang and Laird, 2002). However, lower predicted CVs (30%) in comparison to observed values (62%) likely indicate (i) data smoothing in predicted values by GWR and (ii) the impact of other environmental factors not included in our analysis, such as cryogenic features (high and low centered polygons, pingos, frost boils), organic layer thickness, and fire intensity. Geospatial datasets of these potentially important factors do not exist now, so we could not incorporate them in our spatial prediction approach. The use of these datasets should be evaluated once they become readily available. Because of the modest predictive capability of our method (RPD = 1.8) against the CALM observations (which were not used in the model development), we consider the GWR predicted AL thicknesses presented here to be a first step in the development of our method and one that will benefit from more observations spread across the topographic, edaphic, and climatological gradients known to impact AL thickness.

We compared our predictions with other previously reported observation-based values. Bockheim (2007) analyzed 21 pedons across Alaska that were not included in the dataset applied here and reported an average AL thickness of 0.47 cm (0.30–0.90 m). In a spatial modeling study in the Kuparuk region of Alaska, Nelson et al. (1997) predicted AL thickness from 0 to more than 0.7 m. At seven sites in Alaska, Hinkel and Nelson (2003) predicted AL thickness from 0.20 to 1.2 m using field observations and a linear interpolation algorithm. Our predicted mean and range of AL thicknesses across Alaska (0.14–0.93 m) are within the ranges of these observation-based studies.

Predicted Environmental Controls of Active-Layer Thickness

Across the land cover categories, the largest predicted mean AL thickness (0.54–0.56 m) was found under cultivated and developed land cover types (based on n = 7 and 14 observations, respectively) (Fig. 2a). These categories represent disturbed land cover types and are likely to have thicker AL due to increased thermal conductivity, decreased insulation, and decreased shading. The second highest predicted mean AL thickness was found under forested land cover types (0.39–0.47 m), followed by unaltered (0.27–0.42 m), scrub (0.26–0.41 m), and grassland (0.15–0.50 m) land cover types. The lowest predicted mean AL thickness was found under wetland land cover types (0.15–0.30 m), followed by barren (0.18–0.38 m) and cultivated (0.27–0.37 m) land cover types. The predicted AL thicknesses for each land cover type are shown in Figure 2a. The error bar in the figure represents the standard error.
cover types due to human activities and have reduced natural vegetation cover in comparison to other land cover types. As a result, the annual temperature wave causes soils to thaw at greater depths in these land cover types. Smallest mean AL thickness (0.27 m) was found under barren land cover types (based on \( n = 9 \) points). Barren lands in Alaska are associated with mountainous terrain and higher sloped positions. Mean AL thicknesses of forest \( (n = 29) \), grassland \( (n = 47) \), scrub \( (n = 36) \), and wetlands \( (n = 11) \) were intermediate between the above-mentioned land cover categories (Fig. 2a). Type and coverage of vegetation influence the AL thermal regime and its thickness primarily through altering the surface energy balance by acting as a buffering layer between the atmosphere and the ground (Williams and Smith, 1989). Without separating impacts of different vegetation types, however, Nelson et al. (1997) also reported strong influence of vegetation on mean AL depth in the Kuparuk Basin area of north central Alaska. Consistent with our results, vegetation types were reported as an important component to model the spatial variation of AL thickness (Walker et al., 2003). Increased plant biomass was reported to have a negative relationship with AL thickness because of the insulating effects of vegetation and development of high organic soil horizons (Walker et al., 2003). Also, land cover types were reported to be important controllers of fine resolution spatial variability of AL thickness (Zhang et al., 2012).

The mean predicted AL thickness increased with increasing mean annual air temperature (Fig. 2b). This result is consistent with the results of several former studies and analytical estimates (Stefan and Kudryavtsev equations; Riseborough et al., 2008). For example, at the landscape scale, the AL thickness was strongly correlated with local mean annual air temperature (Hinkel and Nelson, 2003). Mean annual air temperature is often used as a sole predictor of permafrost occurrence for the mapping of large geographical areas (Riseborough et al., 2008). Also, summer air temperature has been widely documented as a principal control on AL thickness (Zhang et al., 1997, 2005). Various authors have used summer air temperature to estimate the annual thawing index and multiplied this index with edaphic factor(s) (e.g., soil conductivity, moisture content, bulk density, latent heat of fusion) to estimate AL thickness over several spatial scales (Romanovsky and Osterkamp, 1995; Nelson et al., 1998; Brown et al., 2000; Hinkel and Nelson, 2003). Despite its extensive use, use of thawing index in predicting AL thickness across regional scales has also been associated with large errors primarily because it doesn’t account for (i) winter and spring warming of soils (Serreze et al., 2000), (ii) key process governing AL thickness such as less winter cooling of the surface soil (Zhang et al., 2005), and (iii) surface morphology and vegetation impacts (Nelson et al., 1997).

Predicted mean AL thickness decreased with increasing slope gradient (Fig. 2c). Topographic attributes including slope gradient have been reported to have strong control over the spatial variability of AL thickness at several scales, as it influences microclimate, hydrology, soil moisture, and vegetation (Hinkel and Nelson, 2003; Riseborough et al., 2008). In nonhuman altered landscapes such as much of Alaska, topographic attributes will be more prominent in describing variability of soil properties in comparison to human altered landscapes. Higher slope gradients indicate well drained soils with lower soil moisture and extremely low thermal conductivity (Nelson et al., 1997, 1998) in comparison to saturated or water-logged soils, which typically have lower AL thicknesses. The negative relationship between AL thickness and slope gradient can also be explained by considering the top-soil thickness as a balance between soil production and erosional processes (Heimsath et al., 1997). That means higher sloped positions in the landscape are more erodible, indicative of shallower top-soil thickness in comparison to lower sloped positions that are less erodible, and indicative of deeper top-soil thickness. Further, higher sloped positions and mountainous landscapes covery in Alaska, both indicative of shallower AL thicknesses.

### Comparing Observation-Based AL Thickness Estimates with Offline Model and Coupled Model Intercomparison Project Phase 5 Predictions

Previously reported offline (meaning uncoupled with a prognostic atmospheric model) land model predictions of AL thickness were deeper than our observation-based predicted values and other reported observations discussed above. For example, Marchenko et al. (2008), using a spatially distributed numerical modeling approach, predicted AL thickness across Alaska to be 0 to 3 m. Schafer et al. (2011), using a climate-scale land-surface model, predicted AL thickness across the entire northern circumpolar region; their predictions for Alaska ranged from 0.8 to 2 m. Our observation-based AL thickness predictions are within the lower range of these large-scale modeling predictions (0.14–0.93 m).

We also compared our results with the coupled CMIP5 earth system model predictions. Making these comparisons was complicated by the fact that, in Alaska, many of the CMIP5 models predicted that permafrost did not exist where the observations suggested it should exist (Koven et al., 2013). We, therefore, selected the top eight of the models based on the closest median AL thickness predictions across Alaska compared to our observation-based estimates (Table 1). Because of these complications, we report the comparisons here to argue that substantial work is required in the land models before they produce believable permafrost temperature predictions, and that there is value to generating observation-based high-resolution estimates for this type of comparison.

Among the eight ESMs analyzed here, GFDL-ESM2G and HadCM3 showed the most realistic representation of AL thickness across Alaska (spatial CVs of 30.5 and 31%, respectively). Although these models did not predict accurate current permafrost extent over the circumpolar region, they reported the lowest bias compared to inferred current climatic controls and circumpolar median AL thickness (Koven et al., 2013). The eight CMIP5 model predictions of median AL thickness across Alaska ranged from 0.35 to 3.4 m, with a spatial CV ranging from 11 to

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47% (Fig. 3). The average of the median prediction of AL thickness across these models was 1.9 m, with a spatial CV of 23%. Our results showed substantially lower (3.5 times) AL thickness (median = 0.54 m) and a different spatial variability in comparison to these estimates when gridded to the same spatial resolution (spatial CV of 28–32%). These comparisons suggest that ESMs substantially overestimate current AL thickness in Alaska, which might result in higher positive permafrost C feedback under future warming scenarios. Without an ability to query the individual ESM models directly, it is not possible to tell what causes the discrepancy between our observation-based results and the model predictions nor is it possible to know whether an ESM with a good comparison to the observation-based estimates has low bias for the correct reasons.

Our geospatial interpolation approach considers the impacts of surface mean annual air temperature, land cover types, and topographic attributes. In a previous analysis of circumpolar AL thickness predictions in CMIP5 models, Koven et al. (2013) focused on surface mean annual air temperature as the primary controller of AL thickness, although other ESM variables were either not represented (topography) or not reported (land cover type). That analysis demonstrated a wide range of AL thickness predictions between models across the circumpolar Arctic, with the differences being attributed to differences in the modeled coupling between (i) near-surface air and surface soil temperatures or (ii) surface and deeper soil temperatures.

When compared with CALM validation datasets, the CMIP5 predictions of AL thickness showed large inaccuracies. The average prediction errors (RMSE and MEE) in four of the compared CMIP5 predictions (BCC-CSM1-1, CanESM2, GISS-E2-R, and MPI-ESM-LR) were several times higher in comparison to GWR estimates (Fig. 4). The remaining four model predictions (FDL-ESM2G, HadCM3, HadGEM2-CC, and HadGEM2-ES) showed larger but relatively comparable prediction accuracies with GWR results. Similarly, the overall predictive quality (RPD) was 1.3 to 36 times lower in CMIP5 predictions compared to GWR.
predictions in comparison to our estimates. These large errors suggest the need for improved process representations and representation of spatial heterogeneity due to local environment (topography, vegetation, and soil properties) in earth system models to generate a realistic variation of regional scale AL thickness, which potentially can reduce the existing uncertainty in predicting permafrost C-climate feedbacks in permafrost regions.

SUMMARY AND LIMITATIONS

In this study, we used soil profile observations, environmental variables, and a geospatial prediction approach to predict the spatial distribution of AL thicknesses at a 60-m spatial resolution across Alaska. The low mean bias of our predictions compared to CALM observations and high RPD illustrate the useful influence of the environmental variables we considered in determining the AL thickness distribution. Further investigation will be required to understand the reasons our predictions led to a higher bias at larger AL thickness and vice versa when compared to the independent CALM dataset. We compared our GWR AL predictions to CMIP5 ESM predictions and found large differences, with the CMIP5 models generally predicting much larger AL thicknesses. Comparisons with several offline models also indicated that our observation-based estimates were typically lower than the model predictions.

Lower predicted spatial variability of our fine-resolution spatially interpolated results compared to the independent CALM observations indicate that the spatial datasets for other soil-forming factors are important for high-latitude environments, such as cryogenic features, time since pedogenesis, fire frequency, and fire intensity. Use of spatial datasets of these variables could potentially increase the accuracy of AL thickness predictions using the geospatial methods applied here. Similarly, the prediction accuracy of our results could also be increased by including additional soil profile samples across the largely unsampled regions of Alaska. Because of these limitations, we consider the observation-based AL thicknesses presented here to be initial estimates that will require future refinement. With these limitations in mind, we believe our fine-resolution predictions of AL thicknesses across Alaska can be a useful resource to evaluate and improve earth system models.

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