DEVELOPING A SOIL INVERSION MODEL FRAMEWORK FOR REGIONAL PERMAFROST MONITORING

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ABSTRACT

Currently, the community lacks capabilities to assess and monitor landscape scale permafrost active layer dynamics over large extents. To address this need, we developed a concept of a remote sensing based Soil Inversion Model for regional Permafrost (SIM-P) monitoring. The current SIM-P framework includes a satellite-based soil process model and a soil dielectric model. We are also working on incorporating a radar scattering model for Arctic tundra into the SIM-P framework. A unified soil parameterization scheme was developed to harmonize key soil thermal, hydraulic and dielectric parameters in the soil process and radar models that can be used in the joint soil-radar inversion framework. The soil parameter retrievals of the SIM-P framework include soil organic content (SOC) and active layer thickness (ALT). Initial tests of SIM-P using in-situ soil permittivity observations showed reasonable accuracy in predicting site-level SOC and soil temperature profiles at an Alaska tundra site and ALT in Arctic Alaska. SIM-P will be further tested using airborne P- and L-band radar data collected during NASA's Arctic Boreal Vulnerability Experiment (ABoVE) to evaluate the sensitivity of longwave radar to active layer properties.

Index Terms— permafrost active layer, soil freeze/thaw, radar inversion, soil dielectric constant

1. INTRODUCTION

Regional warming in the northern high latitudes is occurring at roughly twice the global rate, leading to widespread soil thawing and permafrost degradation [1]. Regional warming and soil thawing may expose vast permafrost soil organic carbon (SOC) stocks to mobilization and decomposition, which may promote large positive climate feedbacks [2]. The timing, magnitude, location, and form of this permafrost carbon feedback (PCF) remain highly uncertain due to many poorly understood mechanisms that control permafrost thaw and subsequent SOC decomposition [3].

Understanding the linkages between soil active layer changes and PCF is hampered by a lack of consistent spatial and temporal information on active layer conditions over regional extents. Detailed process models have been widely used to simulate soil freeze/thaw (F/T) and permafrost dynamics [3-4]; however, regional extrapolation of these models is hampered by multiple factors including large uncertainties in surface meteorology drivers, deficient representations of surface heterogeneity and the processes controlling permafrost dynamics [5]. Other models provide an intermediate level of complexity by relying on a simplified process logic utilizing satellite remote sensing observations as key model drivers, which can be effective in mapping permafrost extent and active layer dynamics [6-7]. However, these assessments are also limited by the coarse resolution of global satellite records, and a lack of direct sensitivity to active layer properties needed for model parameterization and calibration.

Capabilities for direct remote sensing of soil active layer at fine spatial resolution over large scales are still lacking. Low frequency synthetic aperture radar (SAR) remote sensing offers a promising method for such direct observations [8-9]. However, SAR remote sensing of active layer conditions is hampered by the underdetermined nature of radar backscatter, which can be sensitive to a large number of variables in Arctic-boreal landscapes such as snow, ice and vegetation cover [9-11]. The use of multiple radar frequencies and polarizations may reduce uncertainties in the radar inversions, leading to better active layer retrieval accuracy. Extensive coordinated, albeit non-simultaneous, airborne L- and P-band radar backscatter data were collected during the recent Arctic Boreal Vulnerability Experiment (ABoVE) campaigns. Retrievals of critical active layer properties from these observations may enable enhanced

model parameterization and refinement for landscape level mapping and monitoring of active layer conditions.

In this study, we developed a concept of a remote sensing based Soil Inversion Model framework for Permafrost (SIM-P). SIM-P is based on our previous model development, including a satellite-based soil process model [6-7], and a soil dielectric model [12]. A radar scattering model for Arctic tundra [9] will be also incorporated into the SIM-P framework for joint soil parameter retrieval including SOC and ALT.

2. DATA AND METHOD

2.1 Study area and in-situ data

Our study area is Arctic Alaska (>66.55°N, Fig. 1), where multiple in-situ datasets were available to develop and test the SIM-P framework. Airborne P- and L-band radar data in the Alaska North Slope were collected in August and October of 2014/2015, and in May/June and August/September 2017 during the ABoVE Campaign [9].

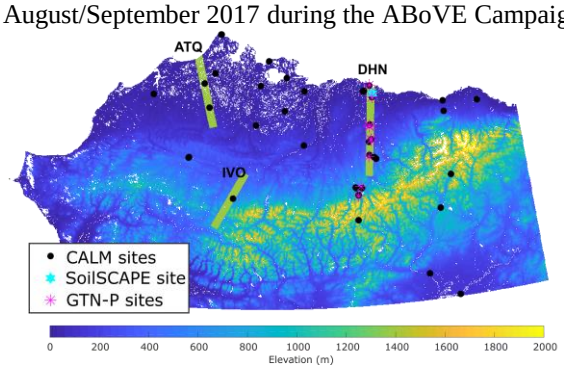

Fig.1 Study area (Arctic Alaska, >66.55° N) and locations of in situ sites used for SIM-P calibration and validation. The airborne SAR flight lines used in this study are shown as green swaths.

Three in-situ datasets were used for model calibration and validation, including half-hourly soil dielectric constant (ε) and temperature (T_{soil}) measurements from a Soil moisture Sensing Controller and oPtimal Estimator (SoilSCAPE) site; 3-hourly ε and T_{soil} measurements from Global Terrestrial Network for Permafrost (GTN-P) sites, and ALT measurements from Circumpolar Active Layer Monitoring (CALM) network. The SoilSCAPE T_{soil} and ε measurements were obtained from different depths (0.05, 0.15, 0.35, 0.56 m) of a wireless sensor network deployed near Prudhoe Bay, Alaska (70°13'47"N, 148°25'19"W) in 2016. SoilSCAPE ε was measured using a METER TEROS 12 soil moisture sensor operating at 70 MHz, while ε at the GTN-P sites was measured using Stevens Hydra Probe sensor at 50 MHz. ε is mainly affected by soil texture, moisture and organic fraction, which are also key factors affecting soil thermal and hydraulic properties [13-14]. ε is a better indicator of soil F/T state than T_{soil}, which is directly sensing to soil liquid water changes (Fig. 2).

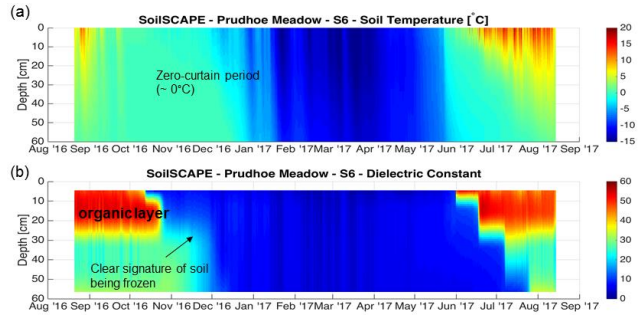

Fig. 2 The in-situ soil temperature (a) and dielectric constant (b) vertical profiles at the Prudhoe Meadow SoilSCAPE site.

2.2 The baseline radar ALT retrieval algorithm

Multiple soil parameters, including ALT and soil moisture (converted from soil dielectric constant), were derived from P-band polarimetric SAR (PolSAR) data obtained in late August and early October [8-9]. The baseline algorithm uses a three-layer dielectric structure and retrieves the corresponding dielectric constants using the time series SAR data. In August, the three layers represent the surface thawed layer, middle and bottom active layer, and the top of the upper permafrost layer. In October, the two surface layers represent a partially frozen active layer with a frozen surface layer overlying a deeper unfrozen active layer. An iterative optimization scheme was used to estimate the soil parameters by minimizing differences between the observed SAR backscatter and radar scattering model simulations:

$$L(X) = \frac{1}{N}\sum_{pp,f}\left(\sigma_{pp,\,mod}(f,X) - \sigma_{pp,\,obs}(f)\right)^2 \qquad (1)$$

where X represents the unknown subsurface parameters to be retrieved, including the thickness and soil dielectric constant of each layer. $\sigma_{pp,\,mod}$ and $\sigma_{pp,\,obs}$ represent the calculated and observed radar backscatter, respectively, at frequency *f*, and polarization *pp* (HH or VV).

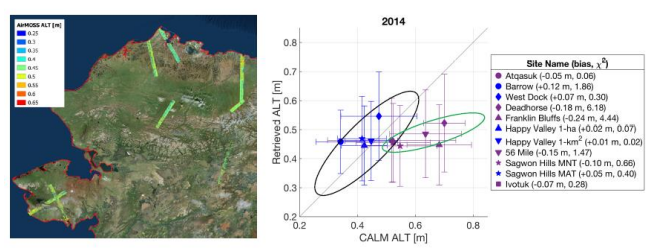

Fig. 3 The P-band radar retrievals using the baseline algorithm for the flight lines in northern and western Alaska. The purple (blue) symbols represent sites where the in-situ ALT is larger (smaller) than the P-band sensing depth (~ 50 cm) [9].

The baseline algorithm retrievals exhibit favorable performance (Fig. 3) compared to collocated CALM measurements with ALT up to ~50 cm (bias < 4 cm), but underestimate deeper active layers (bias ranging from -7 to -23 cm) when in-situ ALT is deeper than the P-band sensing

depth (~50 cm). The baseline algorithm is also underdetermined with more unknowns than observables, leading to ambiguity in radar retrievals [9].

2.3 The SIM-P framework for active layer retrievals

To reduce the ambiguity in the radar inversions, we will introduce additional physical constraints to the radar scattering model imposed by a soil process model [6-7]. Both models share many physical parameters that are required to represent the soil thermal, hydraulic and dielectric properties unique to the permafrost-affected environments. Therefore, we first developed a unified organic soil parameterization [12] that can link the soil process model with the radar scattering model. The soil process model can provide initial estimates of key variables including active layer F/T state and soil moisture (SM), which can be used to estimate the initial soil dielectric profile (key inputs to the radar model). The optimized SOC by the radar model can then feed back into the soil process model, reducing the uncertainties in the estimated dielectric profile. So we can impose joint physical constraints on both models and reduce the ambiguity in the radar inversions.

A SIM-P framework was designed to implement the above ideas (Fig. 4). The current SIM-P framework includes a satellite-based soil process model [6] and a soil dielectric model [12]. The soil process model was developed based on a detailed permafrost hydrology model [4], but has a flexible structure to exploit remote sensing observations including land surface skin temperature (LST), snow cover extent (SCE), and SM as key model drivers and for model parameterization. Multiple soil parameters can be solved iteratively through using in-situ soil dielectric and temperature measurements using the following cost function:

$$L(X) = w1 \sum_{i=1,n1} \left(\frac{T_{mod,i} - T_{obs,i}}{\sigma_{obs}}\right) + w2 \sum_{j=1,n2} \left(\frac{\varepsilon_{mod,i}}{\overline{\varepsilon_{mod}}} - \frac{\varepsilon_{obs,i}}{\overline{\varepsilon_{obs}}}\right) \quad (2)$$

where w1 and w2 represent the weights for T_{soil} and ε cost function, n1 and n2 are the number of T_{soil} and ε measurements. The T_{soil} error was normalized using the standard deviation of in-situ T_{soil} (σ). The simulated annealing algorithm [15] was used for the parameter optimization. The boundary conditions were set as the surface air temperature and the deepest layer depth of T_{soil} measurements. The initial T_{soil} profile at the beginning time step of the model was interpolated from the in-situ data.

Our ultimate plan is to develop a joint soil-radar inversion framework as discussed above, and we are currently working on incorporating the radar scattering model [8-9] into the SIM-P framework (Fig. 4). After implementing this, SIM-P will be able to ingest airborne/satellite radar backscatter data to optimize multiple active layer parameters including ALT, SM and SOC using an iterative solution. We will test the framework using the P- and L-band radar data collected from our pre-ABoVE and ABoVE airborne campaign.

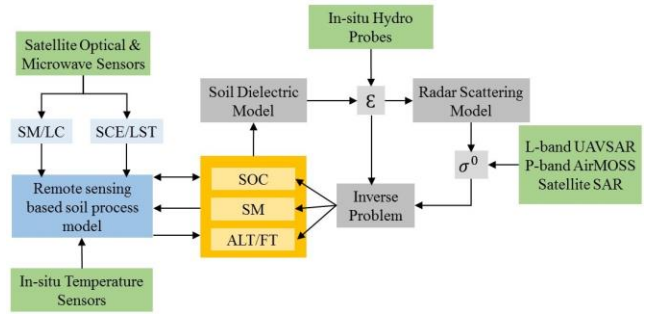

Fig. 4 Processing flow for the remote sensing based Soil Inversion Modeling framework for regional Permafrost monitoring (SIM-P).

3. RESULTS

We tested the SIM-P model at the two nodes (S5 and S6) of the Prudhoe meadow SoilSCAPE site, where detailed T_{soil} and ε measurements were available. The model was run during the 2017 thaw season (DOY 150-270), where enough measurements were available to constrain the inversion. The two nodes show similar ε profiles during the thaw season, but with very different soil temperatures (>5° C difference at 5 cm depth, Fig. 5 a-b).

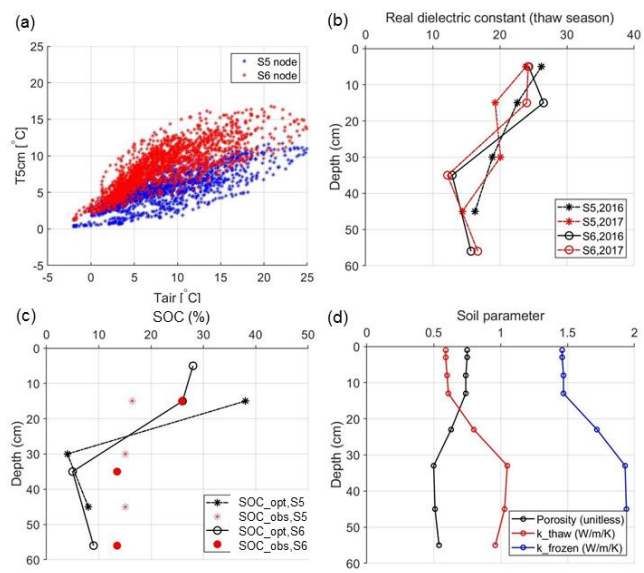

Fig. 5 Model test at the Prudhoe Meadow site: a) in-situ Tair vs T_5cm at two SoilSCAPE nodes (S5 & S6); b) in-situ ε profile; c) Model optimized vs in-situ SOC profile; d) Model optimized soil porosity and soil thermal conductivity (k) profile at S6 node.

The model shows overall higher SOC content in the two surface layers (5-15 cm), compared with the two deeper soil layers (30-56 cm) at both nodes, consistent with in-situ data (Fig. 5c-d). The in-situ T_{soil} at S5 node was much lower than T_{soil} at the S6 node; therefore, the model shows overall higher surface SOC at the S5 node, different from the in-situ

data. However, the in-situ SOC measurements at this site were associated with large uncertainties with only 2 measurements collected along the soil profile. We collected additional soil samples along the Dalton Highway transect in the 2018 summer (with more samples along the profile), which will improve the model evaluation. In addition, the model simulated T_{soil} has a mean RMSE less than 1.5 °C for soil depths from 5 cm to 35 cm.

The soil model was evaluated using regional ALT measurements across Arctic Alaska spanning the period from 2001 to 2016 (Fig. 6). The model slightly overestimates ALT compared with in-situ data from 32 CALM sites, with a mean bias of 10.0 ± 13.2 cm (~20% of mean ALT), and mean RMSE of 15.6 ± 7.7 cm. More than 70% of the sites show significant ($p<0.1$) correlations between the in-situ and model simulated ALT.

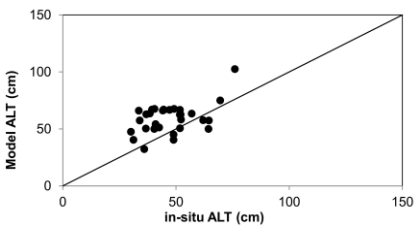

Fig. 6 Comparisons of soil model simulated versus observed mean ALT from 32 CALM sites ranging from 2001 to 2016.

4. DISCUSSION

One major uncertainty in the current SIM-P framework is from the soil dielectric modeling. The model simulated soil dielectric constant profile is generally different from in-situ data, mainly due to uncertainties in the estimates of soil moisture content and the ratio of free to bound water for different soil types [12-14]. The radar backscatter and ε are mostly sensitive to changes in the soil unfrozen water content; a reliable soil dielectric mixing model particularly during the F/T transitional season will be critical to obtain useful information on the active layer properties using multi-temporal radar measurements. On the other hand, the current soil process model does not calculate the soil water balance; instead, it uses the remote sensing based SM product. Current satellite-based SM products generally have difficulty capturing SM changes in the northern high latitudes partly due to insufficient representation of organic soils in the algorithms. Therefore, we will replace the soil process model with a fully coupled permafrost hydrology model [4], to better represent the rapid drying and wetting phenomena generally observed in surface organic soils.

We initially tested the SIM-P framework using only in-situ T_{soil} and ε measurements, while more modeling experiments are needed to examine the sensitivity of P-and L-band radar backscatter to soil active layer properties. Long wavelength radar, including P-band and L-band, is sensitive to vegetation structure, and soil surface and subsurface dielectric properties [10,14]. Our model experiments and analysis using in-situ soil dielectric measurements [7] also indicated potential SAR applications for mapping SOC and F/T profiles. However, vegetation also has a large impact on the radar backscatter, so that distinguishing soil and vegetation contributions to the radar signal remains a challenge. Multi-frequency SAR measurements may reduce uncertainties in the radar soil parameter retrievals by providing contributing information on surface snow, soil, and vegetation conditions [8-11].

5. ACKNOWLEDGEMENTS

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