

ADVANCING AIRBORNE AND SPACEBORNE SYNTHETIC APERTURE
RADAR MEASUREMENTS OF ICE AND SNOW
IN THE NORTHERN GREAT PLAINS

by

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A dissertation submitted in partial fulfillment
of the requirements for the degree

of

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in

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ABSTRACT

The cryosphere is responding to climate change in ways that have negatively impacted socio-environmental systems. Accurate and timely observations of the cryosphere are critical to adapting our infrastructure to these rapid changes. This dissertation contributes novel approaches to validating synthetic aperture radar (SAR) measurements over river ice and seasonal prairie snow.

Previous C-band SAR-based river ice studies typically validate regional ice cover maps using aerial photos of frozen rivers. This qualitative approach relies on the principle that visually rougher ice should result in stronger SAR backscatter. In Chapter 2 of this dissertation I present the first systematic, quantitative investigation of the effect of river ice surface roughness on C-band Sentinel-1 backscatter. I employ Random Forest algorithms first to replicate qualitative classification results from previous studies, and then as regression models to explore relationships between Sentinel-1 backscatter and novel, quantitative surface roughness metrics derived from drone-based Structure-from-Motion datasets. Classification accuracies are similar to those reported in previous studies, but poor regression performance indicates a weak relationship between river ice roughness and Sentinel-1 backscatter. In Chapter 3, I extend these drone-based surface measurements of river ice with GPR-based subsurface measurements. Results from this smaller, richer dataset demonstrate that Sentinel-1 VV backscatter is correlated with ice thickness and VH backscatter with structural properties, but results are site-specific and more work is necessary to create generalized river ice models from Sentinel-1 measurements.

Interferometric SAR techniques have been used to estimate snow water equivalent (SWE) using L-band measurements from the UAVSAR platform. These methods have been developed in mountainous areas and have not been investigated over prairie snowpacks, which typically feature exposed agricultural vegetation and greater spatial variability than found in mountain snowpacks. In Chapter 4 I develop a rigorous statistical framework to demonstrate that UAVSAR measurements over prairie snowpacks are sensitive to small changes in SWE, and are relatively unaffected by exposed agricultural vegetation. However, sub-pixel snow depth variability decreases the accuracy of SWE estimates derived from UAVSAR measurements. The upcoming NISAR satellite mission provides an opportunity to extend this work with repeated L-band measurements over a wider range of prairie snow conditions.

INTRODUCTION

Motivation

The cryosphere is the term for all frozen water on our planet, including sea ice, freshwater (lake and river) ice, glaciers, ice caps and sheets, permafrost, snow, and solid precipitation. These various components are intricately coupled with other elements of the Earth system. For example, the presence of snow or ice on the land or ocean surface greatly increases the surface albedo, which causes a greater percentage of incoming solar radiation to be reflected back into space. As warming temperatures decrease the spatial and temporal coverage of snow and ice globally, more solar radiation is absorbed by the less-reflective surfaces, which results in a positive feedback mechanism leading to more warming and further shrinking of the cryosphere (Curry et al., 1995). The cryospheric response to climate change has negatively impacted socio-environmental systems in the context of water resources, species diversity, and societal health and wellbeing; accurate and timely observations of the cryosphere are critical to adapting our infrastructure to these rapid changes (IPCC, 2019).

Satellite remote sensing is a key tool used to measure snow and ice at global scales, with repeat measurements typically on the order of days to weeks. Algorithms to measure virtually all components of the cryosphere have been developed for a wide array of satellite remote sensors that use different portions of the electromagnetic spectrum (Tedesco, 2015). Active microwave remote sensing platforms, specifically synthetic aperture radar (SAR) sensors, are particularly well-suited for cryospheric monitoring: measurements are not interrupted by nighttime, polar darkness, or clouds, and are typically at spatial resolutions on the order of tens of meters. Current SAR satellites used to measure the cryosphere include

the RADARSAT-2 and Sentinel-1 missions, and NISAR (NASA/Indian Space Research Organization) and ROSE-L (European Space Agency) are two additional platforms with planned launch dates before 2030. These future SAR missions will complement existing satellite technologies and broaden our capability to observe snow and ice at global scales.

The primary goal of this dissertation is to advance SAR measurements of the cryosphere in the Northern Great Plains, using existing technologies to develop future capabilities. Specifically, I focus on river ice and seasonal prairie snow, and employ novel approaches to validate airborne and spaceborne SAR measurements over the ice and snow. Although SAR remote sensing is a common thread between the three chapters of my dissertation, river ice and seasonal snow interact with microwave radiation in very different ways. As a result, I employ different radar instruments and measurement techniques when investigating the different media. In the remainder of the introduction I will discuss microwave interactions with river ice and seasonal snow in more detail.

River Ice

More than one-third of Earth’s landmass is drained by rivers that seasonally freeze over (Yang et al., 2020). The presence of river ice fundamentally changes the ecologic (Thellman et al., 2021), morphologic (Chassiot et al., 2020; Beltaos and Burrell, 2021), and hydraulic (Ettema, 2007) characteristics of a river and adjacent riparian zone. The thermal processes governing the formation (Ashton, 2013) and growth (Ashton and Beltaos, 2013) of different types of river ice are presently well-defined. As air temperatures begin to decline in the later autumn months, two of the first types of river ice to form are border ice and skim ice (Clark, 2013). Border ice originates on river banks and grows horizontally inwards toward the channel centerline. Skim ice is a large, thin sheet of thermally-developed ice that typically forms on the water surface in regions of low turbulence (i.e. low wind and water velocities) and large temperature gradients at the air-water interface. Other types of

surface ice include frazil ice (ice crystals formed when supercooled surface water is entrained downward by turbulent flow), slush or floe ice (collections of frazil crystals joined together as larger masses), and pan or pancake ice (circular clusters of frazil ice that have collided and frozen together in a cohesive unit) (Daly, 2013). Although most river ice develops and exists near the water surface, an exception is anchor ice, which is ice that adheres to the river bottom. Anchor ice forms either through the direct nucleation of supercooled water onto river substrate or by the adherence of frazil particles onto substrate with the help of downward turbulent mixing (Malenchak and Clark, 2013).

After the initial freezeup, various types of river ice often exist simultaneously within the same river reach. Interaction between border ice and ice floes (a general term for free-flowing ice in the water channel) can result in the gradual narrowing of the effective channel width at the surface, often at a bend or constriction in the channel. Over time, accumulations of ice floes or the growth of border ice into an ice bridge can result in channel-wide ice cover (Clark, 2013). As additional ice floes traveling downstream encounter existing ice covers, they either remain on the surface and extend the cover in the upstream direction, or become submerged and travel under the stationary ice cover, often breaking into smaller pieces and adhering to the underside of the ice (Beltaos, 2013a). As an ice cover extends horizontally and vertically, it may grow large enough to become an ice jam, defined by the International Association for Hydraulic Research (IAHR) Working Group on River Ice (1986) as “a stationary accumulation of fragmented ice or frazil that restricts flow.” Ice jams as long as 17 river km (Michel and Drouin, 1975; Kowalczyk and Hicks, 2003) and as thick as 19 m (Beltaos and Dean, 1981) have been documented on various rivers throughout North America.

Ice cover and ice jam formation as described above can happen gradually over the course of a winter season. Later, the characteristics of the transition from winter into spring influence the ice breakup scenario. A gradual, steady warming of air temperatures typically

results in thermal breakup, where much of the river ice melts in place. On the other hand, dramatic shifts in air temperatures or rain-on-snow events can result in rapid increases in river discharge, which can break up the ice before significant thermal deterioration has occurred (Beltaos, 2003). This scenario, called mechanical breakup, is associated with the potential for severe, rapid-onset flooding. As broken ice pieces run downstream, they may jam in a bend or a reach with stronger ice cover and cause backwater flooding. Later, the sudden release of the newly-blocked ice sends a wave of ice and water downstream. The April 2020 mechanical breakup of ice on the Athabasca River in Alberta, Canada resulted in an ice jam more than 20 km in length that formed near the town of Fort McMurray and caused an estimated \$1.1 billion (CAD) in flooding damages, the evacuation of more than 13,000 residents, and one death (Nafziger et al., 2021). Although warming temperatures have resulted in a reduction in the extent and duration of river ice cover globally (Yang et al., 2020), the threat of ice jam floods may actually rise in some areas due to an increase in the number and severity of mid-winter breakup events (Carr and Vuyovich, 2014; Burrell et al., 2021; De Coste et al., 2022; Rokaya et al., 2022). Global monitoring of river ice is critical for managing and adapting to this increased variability.

River Ice-Microwave Interactions

Imaging radars are a type of active remote sensors, where the remote sensing platform emits microwave radiation in the direction of a target and records the signal that is reflected back toward the sensor. This is in contrast to passive microwave remote sensors which record microwave radiation emitted by the target. The spatial resolution of imaging radar instruments is directly related to the length of the antenna and the distance between the instrument and the target (Meyer, 2019). For space-based imaging radars to achieve spatial resolutions sufficient for most science applications ($\sim$ tens of meters), the antennas would need to be on the order of hundreds of meters long, a requirement that is not practical

with current space technology. Instead, synthetic aperture radar (SAR) sensors synthesize a sufficiently long antenna using the orbital motion of the satellite as the instrument makes repeated along-track measurements.

SAR sensors have been integrated into a variety of platforms for the purpose of measuring the cryosphere, including stationary towers (Leinss et al., 2015), cars (Marshall et al., 2022), airplanes (Hensley et al., 2010), and satellites (Chu et al., 2015). SAR sensors can be constructed to operate at a wide range of microwave frequencies, commonly between L-band (down to 1 GHz or ~ 30 cm wavelength) and Ka-band (up to 40 GHz or ~ 7.5 mm wavelength). Incident SAR radiation at different frequencies will have different interactions with the objects or surfaces at the target, which influence the reflected signal ultimately recorded by the instrument. SAR measurements made at lower frequencies typically have lower sensitivities to surface conditions and lower spatial resolutions, but deeper penetration into the surface. Additionally, SAR sensors may have different capabilities with respect to transmitting and receiving waves of different polarizations (horizontal (H) or vertical (V)). Polarization is typically notated with two letters, e.g. VH, where the first letter denotes the transmitted polarization and the second letter denotes the received polarization. Modern SAR sensors for science applications often have dual-polarization capability (HH and HV bands or VV and VH bands), and some provide quad-polarized data (HH, HV, VH, and VV bands). Combining data from multiple polarizations can help discern target surface characteristics (smooth vs. rough, soil moisture content, tall buildings vs. dense tree canopy, etc.) better than using a single polarization.

A number of studies have demonstrated river ice monitoring on regional to global scales using satellite-based SAR data. These SAR-based ice cover maps have been incorporated into operational ice jam flood forecasting (e.g. Gauthier et al., 2006; van der Sanden et al., 2021). Ice jam forecasts typically combine current river ice conditions with forecast meteorological and hydrological conditions. Hence, satellite SAR-based ice maps can provide forecasters

with information about the spatial and temporal evolution of river ice on regional scales, which can help track potentially problematic areas during the spring breakup season. Ice cover maps in previous studies have been derived primarily from the RADARSAT-1, RADARSAT-2, and Sentinel-1 satellite missions. The instruments on these satellite platforms all operate at C-band (5.3–5.405 GHz, or 5.6–5.55 cm wavelength) but have different polarization capabilities (RADARSAT-2 can provide quad-pol measurements while Sentinel-1 is limited to dual-pol VV/VH). The scattering of incident C-band SAR radiation is strongly affected by the physical properties of river ice. Modeling studies (Gherboudj et al., 2008, 2010) have shown that in the case of a homogeneous layer of pure ice with a smooth top surface, the vast majority of microwave scattering occurs at the ice-water interface due to the sharp discontinuity in permittivity between the solid and liquid water. In real river ice, SAR backscatter is also influenced by the roughness of the top and bottom surfaces, as well as structural properties like the presence and distribution of air bubbles, sediment, and other impurities (van der Sanden et al., 2021). These effects are illustrated in Figure 1.1

Most previous studies (e.g. Weber et al., 2001, 2003; Gauthier et al., 2006, 2010) have emphasized the relationship between SAR backscatter and the roughness of the ice cover at the air-ice interface, primarily because this is the most easily observable scattering-relevant ice property. Typically, aerial photos of frozen rivers are used to validate SAR-based ice cover maps (Drouin et al., June 19 - 22, 2007; Chu and Lindenschmidt, 2016; van der Sanden et al., 2021), using the principle that visually rougher ice surfaces will result in a stronger C-band SAR backscatter. This is a purely qualitative validation technique. As I demonstrate in Chapter 2 of this dissertation (Palomaki and Sproles, 2022), quantitative measurements collected using uncrewed aerial vehicle (UAV) Structure-from-Motion techniques reveal that river ice surface roughness is not a strong control on Sentinel-1 SAR backscatter. Chapter 3 extends this work using a novel river ice dataset collected using UAV, ground penetrating radar (GPR), and traditional techniques to examine the influence of ice roughness, thickness,

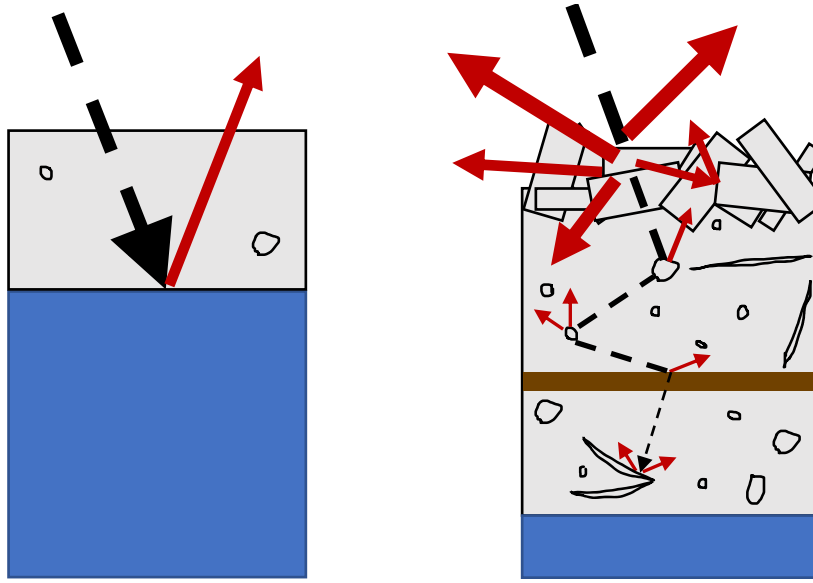


Figure 1.1: Schematic diagram of microwave interactions with river ice. Black dashed arrows represent incident microwaves and red solid arrows represent scattered radiation. Figure reprinted from Palomaki and Sproles (2022).

and structure on Sentinel-1 backscatter. Although the results of Chapter 3 are site-specific, they indicate that the structure of the vertical ice column is a stronger control than surface roughness on Sentinel-1 backscatter. These results

Snow Water Equivalent in Prairie Environments

SAR remote sensing remains a major focus of Chapter 4 of this dissertation, but the application shifts to measuring prairie snow. Optical and hyperspectral satellite-based techniques are well-established for measuring snow properties including snow cover extent (Rittger et al., 2013), optical snow grain size (Nolin and Dozier, 2000), and snow albedo (Bair et al., 2019). However, these methods do not penetrate the snowpack and therefore cannot provide information related to snow depth or snow water equivalent (SWE), the amount of water stored in the snowpack (Lettenmaier et al., 2015). Accurate, high-resolution, global SWE measurements are not currently available (Tsang et al., 2022), and

this missing information represents a major source of uncertainty in climate models (Krinner et al., 2018) and water resource management applications (Siirila-Woodburn et al., 2021).

NASA SnowEx was an seven-year, multi-sensor field campaign with the goal of addressing gaps in snow remote sensing knowledge (Durand et al., 2020), especially remotely-sensed measurements of SWE. Field campaigns were designed to collect coincident remotely-sensed measurements of snow using various UAV and airborne platforms, while high-quality validation data are collected simultaneously using specialized ground-based remote sensing, in situ instruments, and traditional snow pit and snow probe techniques. One of the remote sensing platforms used in SnowEx campaigns was UAVSAR, which features a quad-pol L-band (1.26 GHz, 23.84 cm wavelength) SAR mounted on the underside of a Gulfstream-III jet. These are the same specifications as the L-band SAR on the upcoming NISAR satellite mission; hence, UAVSAR measurements provide an opportunity to lay the foundations for working with NISAR data.

The theoretical basis for SWE retrieval using L-band SAR measurements (described in the next section) was developed with the assumption of a dry, homogeneous snowpack within a SAR pixel. Previous SnowEx campaigns (and most other SAR-based SWE studies) had validation sites concentrated in alpine or tundra snow regimes, where those conditions are generally satisfied during mid-winter. I participated in field work to collect validation data during SnowEx 2021, which was the first year prairie environments were represented in SnowEx validation sites. Prairie snowpack regimes comprise nearly 25% of seasonally snow-covered land area and have distinctly different characteristics compared to alpine or tundra snow environments (Sturm et al., 1995; Sturm and Liston, 2021). In particular, prairie snowpacks are typically shallow and highly variable over short distances. Snow cover and depth in windswept prairie environments are strongly controlled by the presence and height of vegetation (Pomeroy and Gray, 1995). Agricultural producers in these regions retain seasonal snow for use in the spring planting season by maintaining standing crop stubble

over winter (Aase and Siddoway, 1980; Pomeroy and Li, 2000). Hence, snow-covered areas in the prairie often feature exposed agricultural vegetation stubble extending beyond the top of the snowpack (Harder et al., 2019). The work I present in Chapter 4 is the first in-depth investigation of using L-band SAR techniques to measure SWE in prairie environments. Accurate, spatially-distributed measurements of SWE will be critical to support food and fiber production in these regions, especially as climate change shifts viable agricultural zones northward in the coming decades.

Snow-Microwave Interactions

At higher microwave frequencies, SAR radiation interacts with the snowpack in similar ways to those described in Section 1. X- and Ku-band (8–18 GHz, or 3.75–1.65 cm wavelength) SAR measurements are scattered by individual snow grains within the volume of the snowpack and by the snow-ground interface (Tsang et al., 2022). Hence, total backscatter can be related to snow depth and SWE once the snow-ground scattering is accounted for. Recent work (Lievens et al., 2019, 2022) has demonstrated the potential for snow depth retrieval from deeper snowpacks using C-band Sentinel-1 measurements, but the physical mechanisms behind these empirical results remain under investigation; tower-based experiments are currently underway (Brangers et al., 2022).

At lower frequencies, including L-band UAVSAR measurements, a dry snowpack is virtually transparent to SAR radiation and microwave scattering by individual snow grains is negligible. Hence, backscatter data from a single L-band SAR image cannot provide meaningful SWE information (Rott et al., 2003). However, the higher permittivity of snow relative to air causes a signal delay, and therefore a phase change, as the incident microwave travels through the snow medium at a slower speed compared to the theoretical path in a snow-free environment (Gunteriusen et al., 2001). If a snow accumulation or ablation event occurs between two repeat-pass SAR acquisitions, the change in SWE can

be estimated directly from the phase change using L-band interferometric SAR (InSAR) techniques. I present more details behind this physical relationship in Section 4.2, using previously published derivations.

The validation data I helped collect as part of the SnowEx 2021 campaign allows for the first in-depth investigation of L-band InSAR-based SWE measurements in a prairie environment. The field site was the Montana State University Central Agricultural Research Center (CARC), which consists of numerous fields used for agronomy experiments during the growing season. The validation dataset includes snow presence data collected using UAV-based photogrammetry, snow depth data from UAV-based LiDAR and traditional probe methods, and stubble height data at the individual field level. This high-resolution dataset enabled a robust statistical analysis that examines the effects of patchy snow cover and agricultural stubble height, both separately and together, on L-band InSAR SWE retrievals. This work improves our understanding of the feasibility and limitations of L-band snow measurements in prairie environments, and provides guidance for future field campaigns.

Dissertation structure

Chapters 2, 3, and 4 are presented in manuscript form, in the formatting requested by the specific journals. Chapter 2 has been published in *Remote Sensing*, Chapter 3 has been prepared for submission to *Geophysical Research Letters*, and Chapter 4 has been revised and resubmitted to *Remote Sensing of Environment*. I summarize the main findings of these three articles in Chapter 5 and offer some thoughts on the future directions of this work.

QUANTIFYING THE EFFECT OF RIVER ICE SURFACE ROUGHNESS ON
SENTINEL-1 SAR BACKSCATTER

Contribution of Authors and Co-Authors

Manuscript in Chapter 2

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Contributions: Conceptualization, methodology, formal analysis, validation, investigation, resources, data curation, writing—original draft preparation, writing—review and editing, visualization, funding acquisition

Author: Eric A. Sproles

Contributions: Conceptualization, investigation, resources, writing—review and editing, supervision, funding acquisition.

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Article

Quantifying the Effect of River Ice Surface Roughness on Sentinel-1 SAR Backscatter

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Abstract: Satellite-based C-band synthetic aperture radar (SAR) imagery is an effective tool to map and monitor river ice on regional scales because the SAR backscatter is affected by various physical properties of the ice, including roughness, thickness, and structure. Validation of SAR-based river ice classification maps is typically performed using expert interpretation of aerial or ground reference images of the river ice surface, using visually apparent changes in surface roughness to delineate different ice classes. Although many studies achieve high classification accuracies using this qualitative technique, it is not possible to determine if the river ice information contained within the SAR backscatter data originates from the changes in surface roughness used to create the validation data, or from some other ice property that may be more relevant for ice jam forecasting. In this study, we present the first systematic, quantitative investigation of the effect of river ice surface roughness on C-band Sentinel-1 backscatter. We use uncrewed aerial vehicle-based Structure from Motion photogrammetry to generate high-resolution (0.03 m) digital elevation models of river ice surfaces, from which we derive measurements of surface roughness. We employ Random Forest models first to repeat previous ice classification studies, and then as regression models to explore quantitative relationships between ice surface roughness and Sentinel-1 backscatter. Classification accuracies are similar to those reported in previous studies (77–96%) but poor regression performance for many surface roughness metrics (5–113% mean absolute percentage errors) indicates a weak relationship between river ice surface roughness and Sentinel-1 backscatter. Additional work is necessary to determine which physical ice properties are strong controls on C-band SAR backscatter.

Keywords: river ice; synthetic aperture radar; Sentinel-1; structure from motion; surface roughness



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1. Introduction

Seasonal ice cover on high latitude rivers affects the ecology [1], morphology [2], sediment transport [3], and hydraulics [4] of river systems. Perhaps the most consequential aspects of river ice for human society are ice jams and associated flooding. Many types of ice jams and jamming mechanics are well-described [5], and rapid-onset, damaging ice jam floods are often associated with mechanical spring breakup [6]. This scenario occurs at the end of the ice season when a sudden increase in river discharge (e.g., from a rain-on-snow event) causes ice to release from the river channel before significant thermal deterioration of the ice has taken place. As the broken ice pieces run downstream, they may jam in a bend, constrict, or reach with stronger ice cover and cause backwater flooding. Later, the sudden release of the blocked ice sends an ice jam wave (“jave”) of ice and water downstream which can cause rapid flooding. The April 2020 mechanical breakup of ice on the Athabasca River in Alberta, Canada resulted in an ice jam more than 20 km in length that formed near the town of Fort McMurray and caused an estimated C \$1.1 billion in flooding damages, the evacuation of more than 13,000 residents, and one death [7]. These events are difficult to forecast due to the dynamic interactions between many hydrological, meteorological,

and geomorphological factors [8]. Ice jam flood forecasts combine meteorological forecasts and hydrological conditions with the seasonal history and current state of river ice, including information about ice extent, type, and strength [4].

Satellite remote sensing has been used in previous studies to obtain river ice information at regional scales. In particular, synthetic aperture radar (SAR) has proven useful for classifying ice types and tracking ice evolution because microwave scattering is strongly affected by the physical properties of river ice, including surface roughness, thickness, and the presence of impurities (e.g., air inclusions or silt) within ice layers [9,10]. Figure 1 illustrates this effect. Previous studies that have created ice classification maps using fully polarimetric RADARSAT-2 data (e.g., [11–15]) conclude that the highest classification accuracies are achieved when HH polarized data are included in the classification model. For a comprehensive overview of SAR-based river ice studies, see van der Sanden et al. [16].

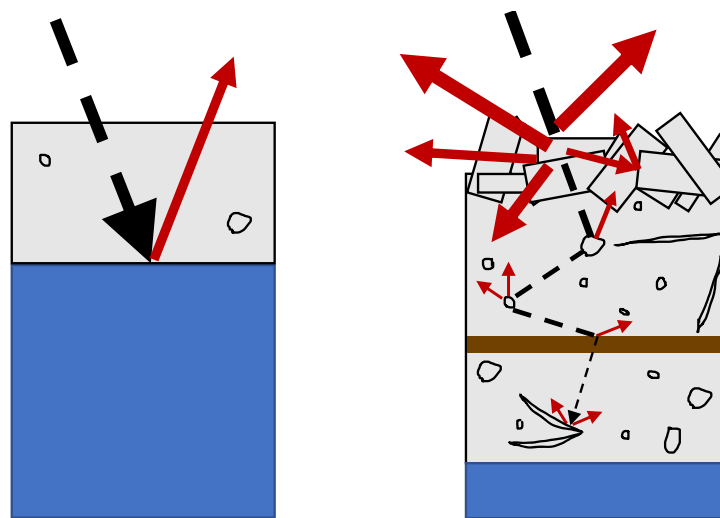


Figure 1. Schematic diagram of microwave interactions with physical properties of river ice. Black dashed arrows represent incident microwaves and red solid arrows represent scattered radiation. In smooth, relatively thin ice with few impurities, incident microwave radiation can penetrate the ice cover and almost all scattering is due to the dielectric change at the ice-water interface. A more complex ice cover contains more scattering mechanisms and results in higher amounts of backscattered radiation.

The roughness of the ice cover at the air-ice interface is the most easily observable among the scattering-relevant properties. Accordingly, ground photos or airplane surveys of frozen rivers have been used as validation data for regional SAR-based ice cover classification [17–20]. Various ice types are delineated via expert interpretation of the photos, typically using visually-apparent changes in surface roughness to distinguish between different types [14,16,21]. The boundaries of the ice classes are digitized and used as labels for training and validation data, then compared to SAR data using supervised and unsupervised classification algorithms. Some studies that use this validation technique have reported global classification accuracies above 90% for some model configurations [12] with accuracies reaching as high as 99% for individual classes [21]. Such robust classification results show that SAR backscatter data contain information derived from the physical properties of river ice. However, this inherently subjective validation method results in ambiguity when interpreting ice maps: it is impossible to quantify the degree to which changes in SAR backscatter are related to surface roughness (visible at the surface) compared to other scattering-relevant properties (changes in ice thickness or structure not visible at the surface). This ambiguity is further complicated by the fact that changes in scattering-relevant properties are not always spatially correlated. For example, field

measurements show that the thickness and roughness of ice jams are related linearly on average, but thickness can also vary significantly over small ($\sim$ m) spatial scales due to the dynamic processes involved in river ice formation [22]. Ambiguity in the interpretation of ice maps with respect to the true ice conditions could lead to inaccurate ice jam forecasts.

With respect to microwave scattering, classification of the roughness of any surface (i.e., smooth vs. rough) depends on the wavelength λ and incidence angle θ of the incident radiation [23]. The roughness of a surface determines the type of scattering, with smooth surfaces resulting primarily in specular reflection away from the sensor and rough surfaces resulting in isotropic scattering, leading to increased backscatter [24]. Surface roughness is typically quantified by calculating the standard deviation h of heights of individual features of a surface. As a general rule of thumb, the features used to calculate h should have a horizontal spacing no greater than $\lambda/10$ [25]. Based on equations given by Sabins [26], van der Sanden and Drouin [23] calculate that for C-band SAR with $\lambda = 0.055$ m and $\theta = 35^\circ$ (representative of RADARSAT-2 data), the ice surface at the air-ice interface is considered radiometrically smooth when $h < 0.0027$ m and rough when $h > 0.0154$ m for surface features separated by distances less than 0.0056 m. These microscale roughness features that affect SAR backscatter behavior are orders of magnitude smaller than the decimeter-scale and larger ice pieces that are physically relevant for ice jam formation. However, validation of SAR-derived river ice products has typically been approached from the perspective of traditional river ice science, which relies on visible changes in surface roughness (thereby emphasizing large roughness features) to denote rough and smooth surfaces [14,20,21]. For SAR-based products to be incorporated into operational ice jam forecasting, this disconnect between radiometrically- and physically-relevant roughness scales must be addressed to reduce uncertainty when interpreting ice cover maps.

In this study, we present the first systematic, quantitative investigation of the effect of river ice surface roughness on the European Space Agency's Sentinel-1 SAR backscatter. The Sentinel-1 platform utilizes the same C-band ($\lambda = 0.055$ m) SAR wavelength as RADARSAT-2, but over land surfaces (i.e., frozen rivers of interest) typically operates in dual-polarized VV and VH mode. Even without the information-rich HH band, Sentinel-1 imagery has been used successfully to derive qualitative river ice information at regional scales [27–29]. Sentinel-1 imagery is also freely available through the Copernicus Open Access Hub whereas there are non-trivial costs associated with acquiring RADARSAT-2 imagery, especially on an operational basis. For ground validation data we use an uncrewed aerial vehicle (UAV)-based Structure from Motion (SfM) photogrammetry [30] to generate high-resolution (0.03 m) digital elevation models (DEMs) of a river ice surface, from which we derive measurements of surface roughness. UAVs have been employed in previous river ice literature to generate training photosets for ice classifiers [31–33], and UAV-SfM has been used to calculate ice surface area and channel-wide fractional ice coverage [34] and to measure ice thickness and volume [35–38]. Importantly, Rødtang et al. [38] established that UAV-SfM accuracy remained consistent across ice-free, freezeup, and midwinter ice conditions, demonstrating that this technique is suitable as a general method to measure all types of river ice. The UAV-based method also improves upon the limitations of traditional river ice photography methods. Ground-based photos provide a limited extent of the frozen river surface at very low viewing angles, which may complicate the interpretation of the image. Airplane-based surveys provide high-quality images over greater extents but come with high operational costs.

We note that the 0.03 m resolution of our UAV-based measurements does not meet the threshold criteria of 0.0056 m (i.e., $\lambda/10$) necessary for separating radiometrically smooth and rough surfaces with respect to C-band Sentinel-1 measurements. However, the two-order of magnitude difference in spatial resolutions between the UAV and satellite datasets allows for an in-depth examination of surface roughness features that are contained within, but not explicitly resolved by, a 10 m Sentinel-1 pixel. Hence, this paper serves as an attempt to quantify the information contained in river ice surface roughness which has been used by expert visual

interpreters in previous studies. We employ Random Forest (RF) regression models for this purpose. We approach this exploration with the following hypotheses:

- RF regression models for river ice surface roughness prediction are not location- or condition-specific; model performance will improve for models trained with data from multiple aerial surveys compared to models trained with a single survey.
- Regression model performance will be affected by the spatial scale at which river ice surface roughness elements are quantified. Finer spatial scales will provide more detailed information content and result in better model performance while coarser spatial scales with less detailed information content will result in worse model performance.
- Regardless of the spatial scale or method used to quantify river ice surface roughness, the roughness will show, at best, a moderately strong correlation with Sentinel-1 backscatter because other physical properties related to ice structure that affect the backscatter signal are not measured by the UAV-SfM method, and therefore not accounted for in the models.

Exploring these hypotheses can enhance ice jam forecasts by improving our understanding of the river ice information contained in SAR imagery. If SAR backscatter is strongly controlled by ice roughness, traditional visually-based validation can still be utilized for ice classification maps and ice jam forecasters can incorporate roughness information into their forecast models. Finding a weak relationship between SAR backscatter and ice roughness could help guide future field campaigns to target measurements of ice properties that are more relevant with respect to SAR imagery, for both current and future sensor platforms. The remainder of the paper is organized as follows: Section 2 details our methodology for UAV aerial surveys, surface roughness measurements, and RF analysis; Section 3 contains results, which are discussed in Section 4; finally, we conclude the study briefly in Section 5.

2. Methods

Our measurements of river ice surface roughness are derived from high-resolution, SfM-based DEMs generated from UAV aerial surveys. Before we investigate quantitative relationships with Random Forest (RF) regression models, we must first verify that RF models in general are appropriate to use with our novel dataset. Without this verification it would be difficult to interpret poor regression performance: are the poor results because the observed surface roughness values have little influence on the SAR backscatter, or are they due to a poorly-chosen model for the dataset?

For this reason, we begin our analysis with RF classification, a supervised technique which has been used successfully to classify river ice using Sentinel-1 imagery [29]. Demonstrating that RFs can classify our novel dataset with acceptable accuracy provides a straightforward interpretation of RF regression results. We create various quantitative metrics with UAV-derived surface roughness measurements to describe the roughness characteristics within the Sentinel-1 pixels in different ways. We also investigate the effect of summarizing the UAV-derived roughness information at different spatial scales, and explore how these different expressions affect RF regression performance.

2.1. Study Site and Ice Conditions

Our study site was a short reach ($\sim 0.25 \text{ km}^2$) of the Yellowstone River near Glendive, Montana, USA (Figure 2). The Yellowstone is the longest uncontrolled river in the continental United States (1114 km) and drains approximately 100,000 km^2 of the land area into the upper Missouri River. The channel at our site is approximately 200 m wide and features a large bend. The site has straightforward river access, a multi-decadal history of ice jam formation, and lies in the imaging path of the Sentinel-1B satellite. Strong, gusty winds ($> 10 \text{ m s}^{-1}$) are typical of the winter months and impede regular UAV operations in the area. Flight dates were planned around Sentinel-1B flyovers that also aligned with fair weather and less windy conditions. We completed two aerial surveys of the site on 19 February and 4 March 2021 before Sentinel-1B went offline in December 2021.

The 19 February aerial survey captured typical midwinter ice conditions. Trace amounts of snow were recorded on 17 and 18 February at the nearby Dawson Community Airport weather station and air temperatures remained at or below freezing during those days. On 19 February a thin (~ 0.05 m) layer of dry snow was present on top of the river ice at the study site. During the ~ 2 h aerial survey on 19 February, air temperature ranged from approximately -20 to -16 °C, and wind speeds increased from calm to approximately 8 m s^{-1} with stronger gusts, which terminated operations before the entire survey could be completed.

Conditions during the 4 March aerial survey were more representative of the spring transitional period. From 1–3 March daytime high temperatures were above freezing for several hours, with overnight lows dropping back below freezing. It is assumed that the top of the ice surface exhibited diurnal changes during this period, with liquid water appearing during the day and refreezing overnight. The dry snow layer present on the ice during the 19 February survey had either melted or metamorphosed into patchy, wet snow cover by the time we conducted the 4 March survey. Air temperatures increased from below to above freezing and winds remained calm during this full survey.

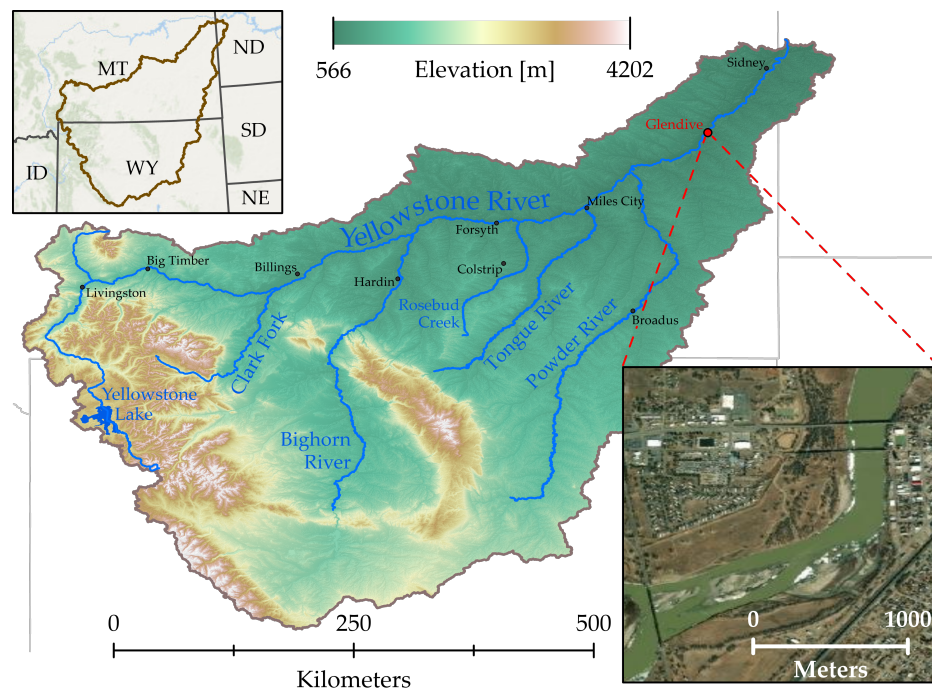


Figure 2. Yellowstone River watershed. The Yellowstone River drains approximately 100,000 km² of land area in Montana, Wyoming, and North Dakota, USA, into the upper Missouri River via the Yellowstone River and its major tributaries, the Powder, Tongue, Bighorn, and Clark Fork Rivers, and Rosebud Creek. Our study site is located on Yellowstone in Glendive, Montana (bottom right panel). Satellite imagery ©Maxar Technologies.

2.2. UAV Surveys, SfM Processing, and Surface Roughness Calculations

We designed aerial surveys for our study so that the final SfM products would achieve <0.1 m spatial resolution, two orders of magnitude finer than Sentinel-1 backscatter data. We used a commercially-available Vision Aerial Switchblade-Elite tricopter UAV with an integrated Real Time Kinematics (RTK) GPS unit and a Sony $\alpha 6000$ 24.3-megapixel camera payload. We flew pre-planned gridded flight paths at 80 m above ground level with 70% front and side image overlap. The planned survey resulted in 1251 overlapping photos geotagged with latitude, longitude, and altitude information. The 19 February photoset

contains only 985 photos because inclement weather prevented us from surveying the entire site. The 4 March photoset contains all 1251 photos. On each field date, we also surveyed at least 6 ground control points on riverbanks and other ice-free areas using Emlid Reach RS2 RTK GNSS receivers to further reduce the georeferencing error.

SfM processing was completed using Agisoft Metashape Professional v1.6.2 [39]. We followed the procedure and suggested processing parameters detailed by Over et al. [40]. The final root-mean-square reprojection error was 0.135 m and 0.131 m for the point clouds used to generate the 19 February and 4 March products, respectively. The SfM-derived products used for further analysis were an orthomosaic photo and a DEM of the study site from each flight date. The native resolution of the DEMs were 0.028 m and 0.030 m for the 19 February and 4 March surveys, respectively. Both DEMs were aligned and exported at 0.03 m resolution for further analysis.

Within the river channel portion of the DEMs, we calculated surface roughness at every pixel as the standard deviation of elevation within a 3×3 moving pixel window. We chose the smallest window size possible to minimize artificial smoothing of the finely-detailed information present in the DEM. The use of a moving window resulted in surface roughness data at the same 0.03 m spatial resolution as the raw elevation data.

2.3. Sentinel-1 Imagery

Our field site was imaged by the Sentinel-1B platform on 18 February and 2 March at around 18:00 local time (MDT). The two satellite images were acquired approximately 12 h and 36 h before our aerial surveys on 19 February and 4 March, respectively. We downloaded the Ground Range Detected (GRD) products for both images from the Alaska Satellite Facility Vertex Distributed Active Archive Center. We preprocessed the GRD images by applying an orbit file, radiometric calibration, radiometric terrain flattening, and range-doppler terrain correction to obtain VV and VH backscatter intensity in terms of γ_0 with units of dB. γ_0 has been used in previous river ice SAR studies [16,29] because it is less sensitive to changes in radar incidence angle than other measures of backscatter [41]. All image pre-processing was completed using the ESA SNAP software v8.0 [42]. Figure 3 shows a comparison of Sentinel-1 VH backscatter alongside UAV orthoimagery and surface roughness measurements.

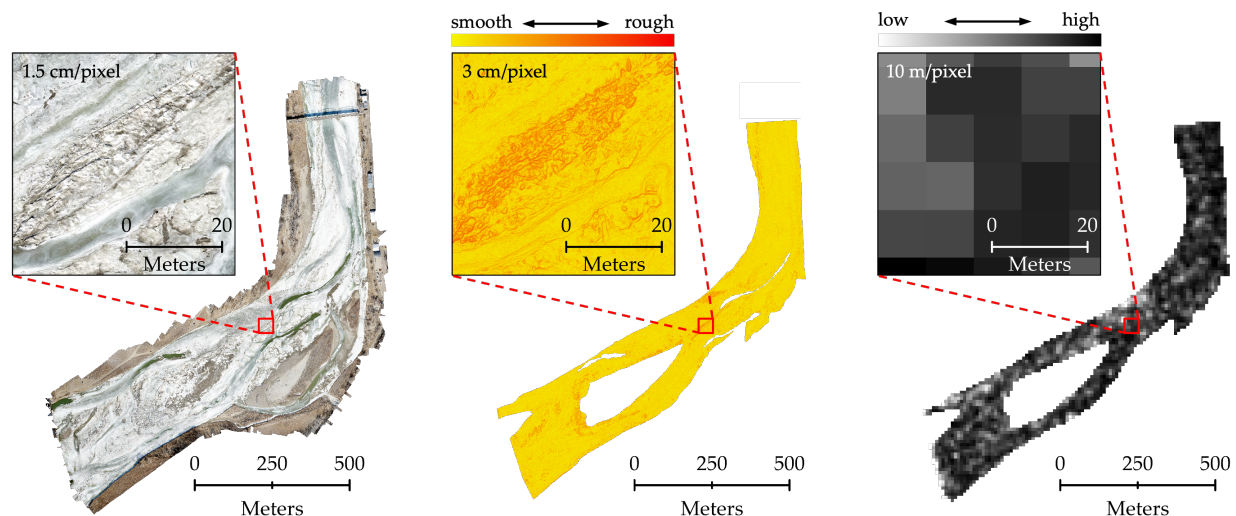


Figure 3. (Left) UAV orthoimagery of the field site on 4 March 2021, including river ice, small open water leads, islands, and riverbanks. (Middle) Surface roughness measurements derived from 4 March UAV DEM, clipped to the ice surface. (Right) Sentinel-1 VH backscatter from 2 March clipped to the ice surface.

For the purposes of using Sentinel-1 data as predictor variables, we created additional derived products from the VV and VH bands: the inverse and square of each band, and the product and ratios of both bands, for a total of eight predictors (Table 1). This type of feature engineering is a common step in machine learning studies [43]. These eight predictors comprise the Sentinel-1 data used to predict ice type in RF classification experiments and measured surface roughness in RF regression experiments.

Table 1. Sentinel-1 predictor variables used in Random Forest classification and regression models.

Type	Name	Formula
Raw	VV	—
	VH	—
Derived	VV inverse	$1/VV$
	VH inverse	$1/VH$
	VV square	VV^2
	VH square	VH^2
	Ratio 1	VV/VH
	Ratio 2	VH/VV
	Product	$VV \cdot VH$

2.4. Random Forest Classification

Here we adopt the typical validation strategy of visual interpretation of the UAV-derived orthoimagery. Following de Roda Husman et al. [29] and van der Sanden et al. [16], we initially selected rubble ice (relatively rough), sheet ice (relatively smooth), and open water as the three target classes. We created polygons in ArcGIS Pro marking areas of the three classes in the SfM-derived orthophotos, then overlaid the Sentinel-1 imagery. We discarded any Sentinel-1 pixels that imaged areas outside the boundaries of the frozen river channel to remove backscatter measurements affected by vegetation, bare ground, and built structures. We classified the remaining pixels using an area thresholding technique, where a class label was assigned to a pixel if the label comprised a larger percentage of the pixel's area than the threshold value (e.g., 50%). This threshold value potentially has a large effect on classification performance: higher values result in more distinct groups, but come at the expense of smaller datasets available to train and test the models. We optimized classification accuracy by experimenting with a range of area threshold values from 50% to 100%. We also note that individual pixels in an input dataset with the same class label are not necessarily spatially adjacent.

Ice conditions at the study site featured very few open water leads and even with the lowest area threshold value of 50%, only 14 Sentinel-1 pixels were classified as open water between both survey dates. This proved to be an insufficient number of samples to generate reasonable classification results and so the open water class was dropped from consideration. To test the general applicability of the classification model on the two remaining classes (sheet ice and rubble ice) we conducted three model runs trained using different datasets: samples from the two survey dates individually, and a third dataset combining the samples from both dates. The individual-date models were not exposed to samples from the other date during either the training or testing phases. We ran each of the three model configurations 100 times, where the input datasets were randomly divided into a 70%/30% train/test data split during each run. Classification accuracy in Section 3 is calculated using the combined output from all 100 model runs.

We implement the RF algorithm using scikit-learn [44], a Python machine learning package. Like most machine learning algorithms, RFs contain a number of hyperparameters that provide the modeler control over the architecture of the algorithm and the computing resources required to train the model. Hyperparameter values are user-specified prior to running the model (i.e., not derived from the input dataset) and can affect model accuracy and other performance measures. Two RF hyperparameters that should be adjusted are the number of decision trees in the forest ('n_estimators' parameter in the scikit-learn

implementation) and the number of predictor variables that should be considered at each split in each tree ('mtry' parameter) [45]. The default 'mtry' value in scikit-learn is set as the square root of the number of predictor variables, and several studies have concluded that this is generally a reasonable value [46]. After an extensive review of the literature, Belgiu and Drăguț [47] suggest a value of 500 trees when using RF classification with remotely sensed data. Our specific model architecture (along with all code and data necessary to repeat the model) can be found in the GitHub repository for this project [48].

2.5. Random Forest Regression

The input dataset for RF regression consists of all available river ice surface roughness measurements and is not based on subjective visual interpretation of ice classes. To compile the dataset we began by selecting only Sentinel-1 pixels from both survey dates that imaged an area 100% covered by ice. This removed backscatter measurements affected by vegetation, bare ground, and built structures. We additionally masked pixels that covered the small areas of open water or bright, homogeneous snow cover. The SfM algorithm cannot locate tie points within these surface types and the resulting DEM contains erroneous elevation values. After clipping and masking we retained 1371 Sentinel-1 pixels that aligned with ice in the 19 February aerial survey and 2320 pixels for the 4 March survey, for a total of 3691 pixels.

Each 10 m Sentinel-1 pixel contains more than 100,000 UAV surface roughness measurements at the 0.03 m spatial scale. However, RF regression models require training data in the form of one-to-one mapping between the target (surface roughness) and predictor variables (Sentinel-1 products). For our study, this requires that within each Sentinel-1 pixel we transform the 100,000 UAV measurements into metrics that represent the fine-scale surface roughness information as a single numerical value. Many transformations are possible and we create two broad suites of surface roughness metrics. Metrics in the first suite can be described as either spatially-based or distribution-based. For the single spatially-based metric, we calculated Moran's I statistic [49], a measure of spatial autocorrelation, for the UAV measurements inside each Sentinel-1 pixel using ArcGIS Pro. In the distribution-based approach, we fit a log-normal curve to a 100-bin histogram of the UAV measurements contained within each Sentinel-1 pixel. We extracted the means and standard deviations of the estimated distributions as roughness metrics to be used for regression targets.

The second suite of metrics was developed to explore the effects of downsampling the UAV roughness measurements at different subgrid spatial scales with respect to the 10 m Sentinel-1 pixels. Figure 4 illustrates the process of deriving these subgrid-statistic roughness metrics. First, we create a new raster grid at an intermediate spatial scale (0.25, 0.5, 1, 2, or 5 m) overlaid on the 10 m Sentinel-1 grid. We resample the 0.03 m UAV measurements to the intermediate grid using a variety of statistics (maximum, median, minimum, range, 5th percentile, and 95th percentile) to emphasize different aspects of the roughness features. Finally, we downsample the intermediate roughness values to a single value in the native 10 m Sentinel-1 resolution using a final aggregation operation (maximum, minimum, and mean). For completeness we also calculate the maximum, median, minimum, range, 5th percentile, and 95th percentile roughness at 10 m resolution directly from the UAV data, skipping the intermediate subgrid step and removing the need to apply a second aggregation operation.

As in the RF classification, we tested the general applicability of the regression models by training/testing models using roughness metrics from the two survey dates individually, plus a third dataset combining metrics from both dates. We ran each of the three model configurations 100 times, where the input datasets were randomly divided into a 70%/30% train/test data split during each run. We increased the number of trees in the forest ('n_estimators' parameter) to 2000 for regression models, above which the reduction in regression error is negligible [50].

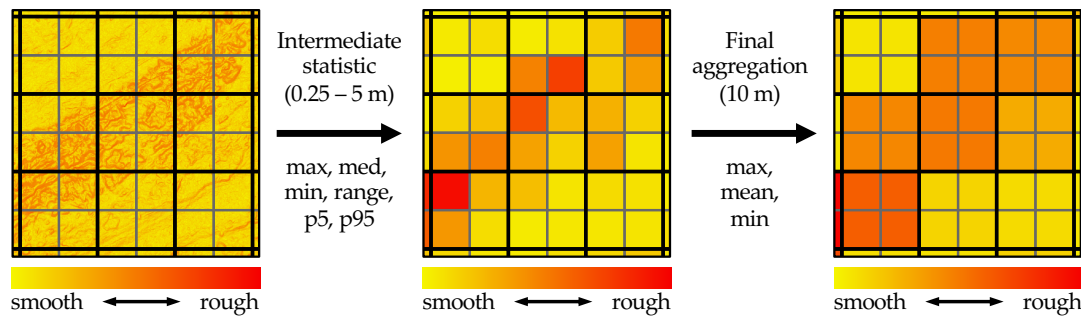


Figure 4. Example derivation of roughness metrics from raw surface roughness measurements. In this example, the (left panel) shows the 0.03 m surface roughness measurements (yellow–red), a 5 m intermediate resampling grid (thick gray lines), and the 10 m Sentinel-1 pixels (thick black lines). The (middle panel) shows the roughness measurements resampled to the intermediate grid after taking the maximum roughness measurement inside each 5 m pixel. The (right panel) shows the final roughness metric at the 10 m resolution, calculated by taking the mean of the intermediate 5 m values inside each 10 m pixel.

3. Results

3.1. Surface Roughness Measurements

Figure 5 shows the observed probability density functions (PDF) and cumulative density functions (CDF) for UAV-derived river ice surface roughness measurements on the 19 February and 4 March, displayed on a logarithmic x-axis. The density functions were computed using every UAV measurement contained within the 3691 Sentinel-1 retained for the regression models (approximately 410 million observations). For both survey dates, surface roughness measurements vary over several orders of magnitude from fractions of a millimeter to a few centimeters. While these measurements seem relatively small, it is important to remember that they represent the standard deviation of elevation in a 0.09×0.09 m area on the ice. Roughness measurements from both survey dates appear to approximate log-normal distributions. The 19 February PDF is centered at approximately 0.0019 m and has a larger standard deviation (i.e., the curve appears wider) than the 4 March PDF, which is centered at approximately 0.0011 m. This indicates a greater range of river ice surface roughness, and also rougher ice on average, on 19 February than on 4 March. Hence when these measurements are the basis for regression targets, models trained with the 19 February data will be exposed to a wider dataset domain than models trained only with the 4 March data.

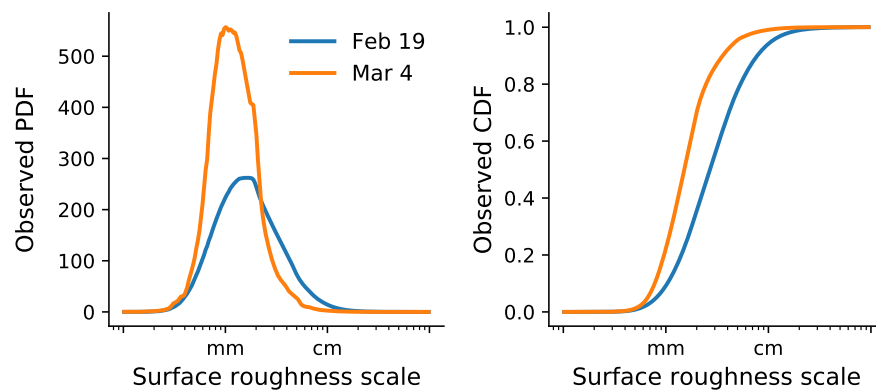


Figure 5. Observed probability density functions (PDF) and cumulative density functions (CDF) for UAV-derived river ice surface roughness measurements on 19 February and 4 March 2021.

3.2. Random Forest Classification

Figure 6 shows the observed PDFs and CDFs of surface roughness measurements for the sheet ice and rubble ice class samples selected from the two aerial survey dates with an area threshold value of 50%. Roughness PDFs for sheet ice and rubble ice overlap on both dates, but there is a larger separation between the classes in the 19 February samples (Figure 6, top row) than in the 4 March samples (Figure 6, bottom row). This result is not surprising given the relative shapes of the density functions containing all roughness measurements on the two survey dates (Figure 5).

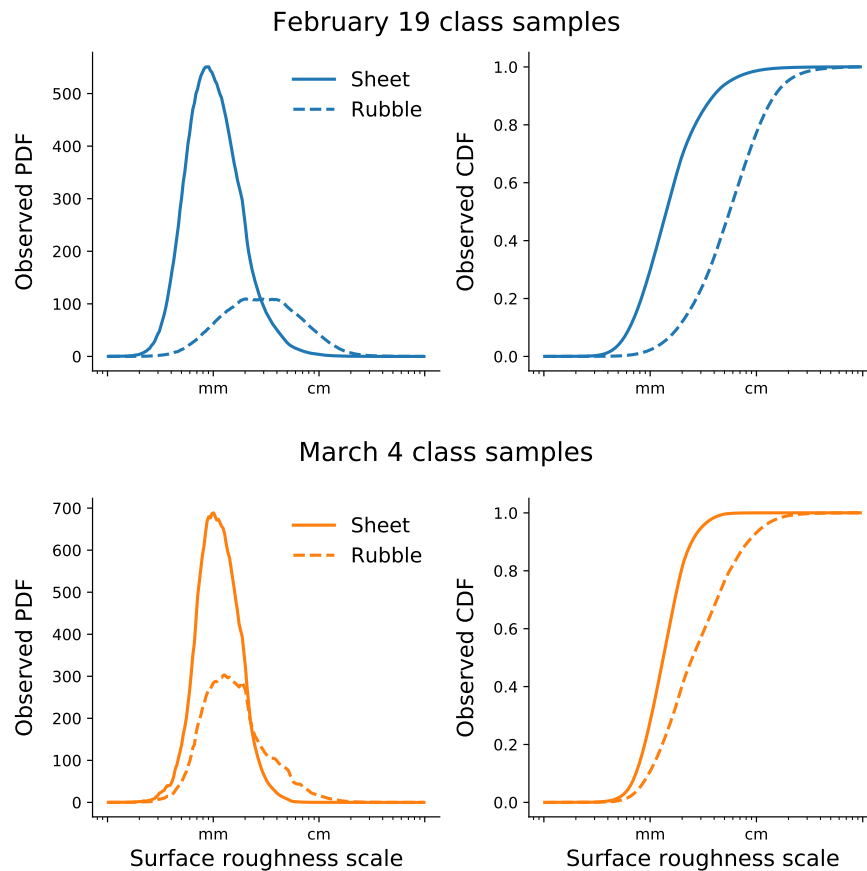


Figure 6. Observed probability density functions (PDF, left column) and cumulative density functions (CDF, right column) for UAV-derived river ice surface roughness measurements for visually-determined sheet ice and rubble ice class samples from the 19 February (top row) and 4 March (bottom row) aerial surveys.

Figure 7 shows RF classification accuracies using a variety of training datasets and classification area threshold values. Fewer samples are available to include in the training datasets as the class area threshold increases. 80 samples of sheet ice and rubble ice (160 samples total) were selected from each date with an area threshold of 50%, down to 24 samples of both classes (48 samples total) with a threshold of 100%. Note that samples from both dates are merged for the combined-date model, so the training datasets are twice as large as compared to those for the single-date models. For the 19 February model, accuracy generally increases as the threshold increases, but the 4 March model has a peak at 70%. This indicates that increasing the area threshold creates more separation between samples in the two classes, and therefore it is easier for the model to classify correctly. However, with our relatively small dataset there is a point where the total sample size

becomes too small to properly train the classifier. The optimum threshold value for our dataset appears to be 70%, where the 19 February model achieves 96% and 94% accuracy for sheet ice and rubble ice, the 4 March model achieves 78% and 87% accuracy, and the combined model achieves 83% and 77% accuracy.

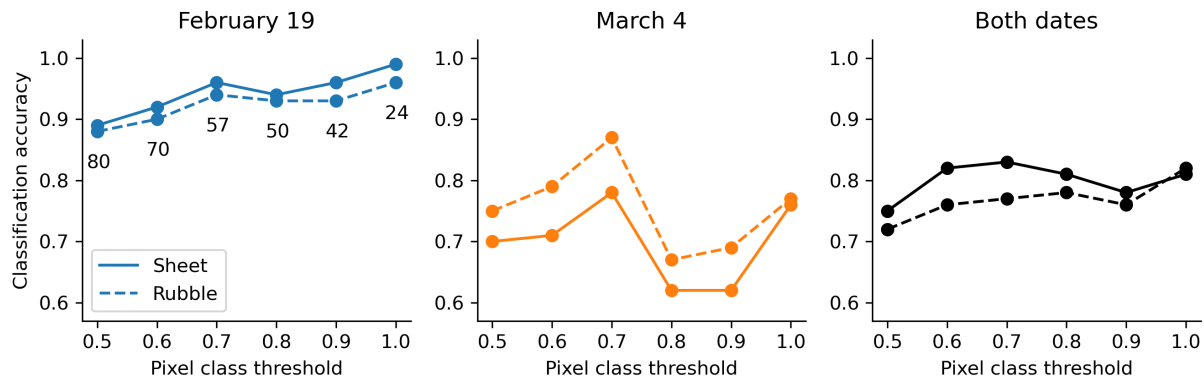


Figure 7. RF classification accuracy for sheet ice (solid lines) and rubble ice (dashed lines) using models trained with data from 19 February only (**left panel**), 4 March only (**middle panel**), and both dates combined (**right panel**). The numerical labels in the 19 February panel denote the number of samples selected from each class on each date in the overall dataset.

3.3. Random Forest Regression

Figure 8 shows RF regression results for Moran's I statistic, estimated log-normal mean, and estimated log-normal standard deviation for models trained/tested on surface roughness measurements from 19 February only (left column), 4 March only (middle column), and both dates combined (right column). Red dashed lines in each figure are 1-1 lines representing perfect regression accuracy. Noted at the top of each figure are the mean absolute percentage error (MAPE) and R^2 values for the model configurations. Similar to classification results, reported MAPE values are calculated as the average MAPE after 100 RF model runs, where the input dataset is randomly divided into a 70%/30% train/test data split during each run. All regression targets for all model configurations exhibit a considerable amount of spread. MAPE values range from 9–29% and the error values for the combined-date models are approximately the average of the error values for the two individual-date models. Overall errors for a single target are lowest for the estimated log-normal standard deviation but highest for the estimated log-normal mean.

We prefer to use MAPE as our model assessment metric in this context because it enables an intuitive comparison of the relative error between the many different regression targets. We include R^2 values in these regression figures to demonstrate that this metric is misleading and inappropriate for our results. For all targets, the R^2 value for the combined-date regression model is higher than either of the individual-date models. This is not because the combined-date model performs better, but because a larger training dataset results in a larger number of points used to compute the metric for this model configuration. We suggest that future studies consider this possibility and choose a more appropriate metric such as MAPE to assess regression performance.

Figure 9 shows RF regression results for a single subgrid-statistic roughness metric. The first step in the derivation of this metric was calculated as the median surface roughness at a 0.25 m subgrid resolution (i.e., moving from the left panel to the middle panel in Figure 4). The three rows of plots in Figure 9 represent regression results for these intermediate measurements aggregated using the three different aggregation operations (i.e., moving from the middle panel to the right panel in Figure 4 using maximum, mean, and minimum aggregation operations). Note that the three rows have different y-axis limits, which altogether span two orders of magnitude. The columns in Figure 9 again represent

RF models trained with input data sets from 19 February only (left column), 4 March only (middle column), and both dates combined (right column). Although significant spread is present in the regression results of all nine model configurations, the 4 March data are more tightly clustered than the 19 February data for all aggregation operations. This is an intuitive result when considering the density functions for surface roughness measurements from the two survey dates (Figure 5). Data outliers are largest for the datasets derived using maximum final aggregation (top row) and smallest for datasets derived using minimum final aggregation (bottom row), which correspond to the highest and lowest MAPE values, respectively. Figures similar to Figure 9 for all subgrid-statistic regression targets can be found in the Supplemental Data. Although MAPE values change slightly for other subgrid-statistic targets, regression model performance for all targets follows the general patterns discussed above.

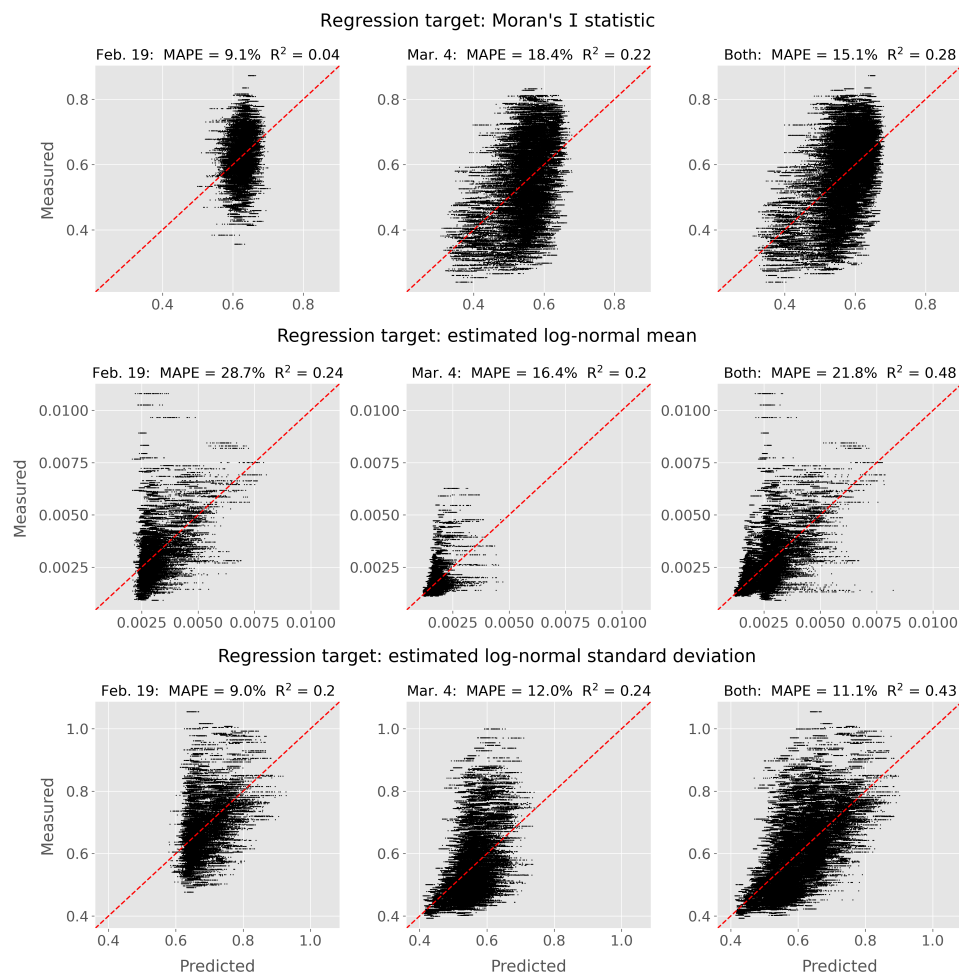


Figure 8. RF regression results for Moran's I statistic and estimated log-normal mean and standard deviation distribution parameters. RF models are trained with input data sets with samples from 19 February only (left column), 4 March only (middle column), and both survey dates combined (right column). Red dashed lines are 1-1 lines representing perfect regression accuracy.

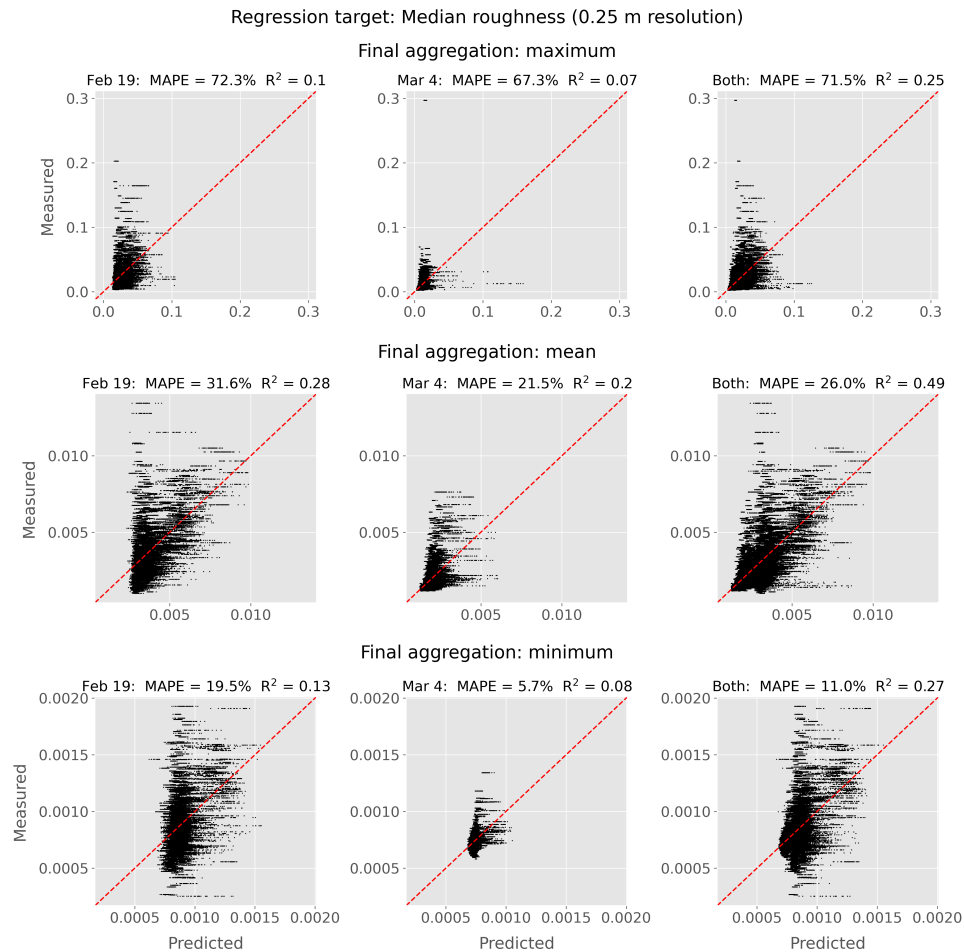


Figure 9. RF regression results for median surface roughness calculated at a subgrid resolution of 0.25 m. RF models are trained with input data sets with samples from 19 February only (**left column**), 4 March only (**middle column**), and both survey dates combined (**right column**). The final operations applied to aggregate the subgrid roughness metrics at the 10 m Sentinel-1 scale are the maximum (**top row**), mean (**middle row**), and minimum (**bottom row**). Red dashed lines are 1-1 lines representing perfect regression accuracy. Note the different y-axis limits between the three rows.

Figure 10 shows a summary of MAPE values for RF regression models trained to predict all subgrid-statistic targets. The nine scatter plots shown in Figure 9 correspond to a single colored cell in each of the nine grids in Figure 10 ('med' summary statistic on the x-axes and 0.25 m subgrid scale on the y-axes). The other colored cells in the nine grids represent MAPE values calculated for other subgrid-statistic roughness metrics, for which detailed scatter plots are available in the Supplementary Data. Rows of grids again separate targets by the final aggregation operation and columns of grids again separate models trained with samples from 19 February only (left column), 4 March only (middle column), and both survey dates combined (right column). Errors are generally higher for the 19 February models compared to the 4 March models, and errors for the combined model are approximately the average between the two individual-date models. The models tend to perform better (i.e., errors decrease) when trained on targets that emphasize the left tail of surface roughness distributions. This pattern is evident at the level of the target metrics (errors are lower for minimum and 5th percentile targets than maximum and 95th percentile targets) and at the level of final aggregation (errors are lower when aggregating by

minimum subgrid roughness than by maximum subgrid roughness). For targets with mean and minimum operations for final aggregation, model performance generally improves as the subgrid spatial scale becomes finer. The opposite trend is apparent for targets aggregated by maximum roughness, where MAPE values increase as the subgrid-scale becomes finer. Note that for target metrics originally calculated at 10 m spatial resolution (the top row of cells in each larger grid), model performance does not change with the final aggregation statistic because no operation is required to aggregate the data to the Sentinel-1 grid. Grey cells that do not contain MAPE values represent redundant model runs: for example, calculating the maximum of 1 m subgrid cells and then aggregating to 10 m by again applying the maximum is equivalent to simply calculating the maximum of the original 10 m cell. This type of redundant model run was not conducted and is excluded from analysis.

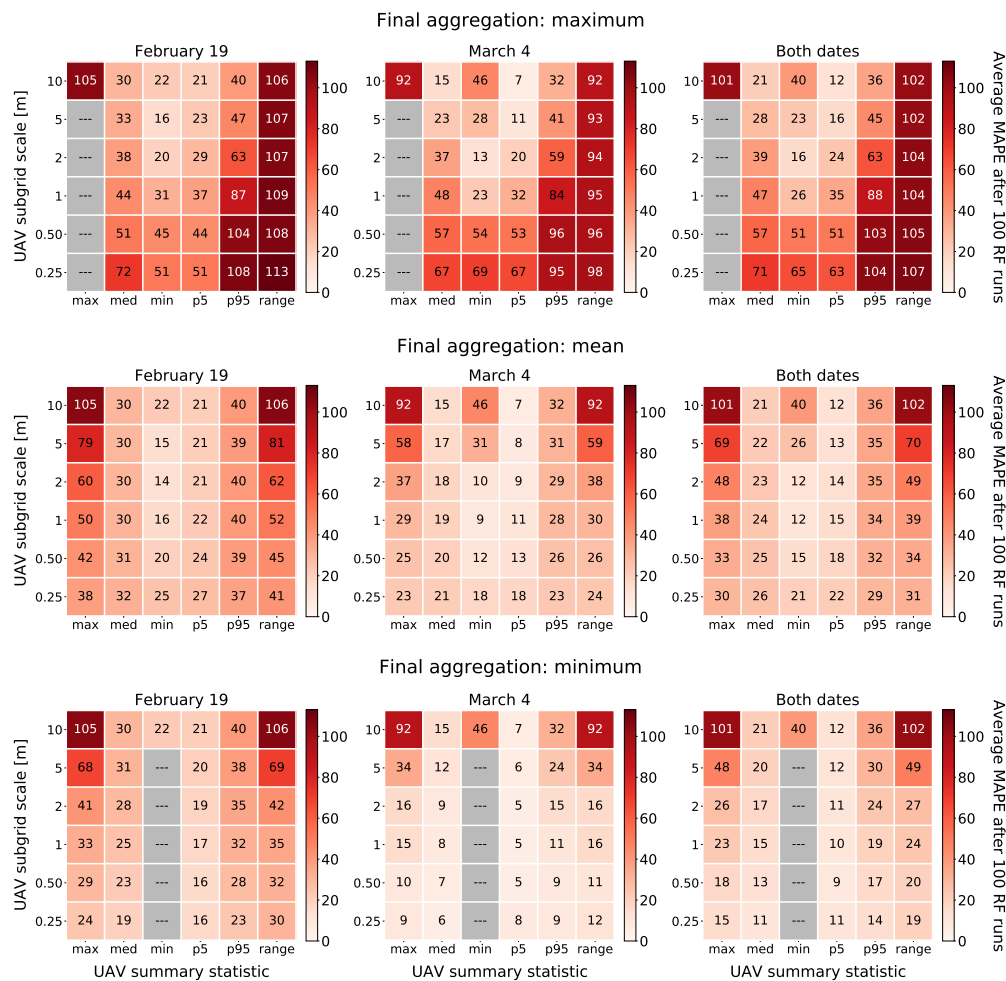


Figure 10. Mean absolute percentage error (MAPE) for RF regression targets for RF models trained with input data sets with samples from 19 February only (left column), 4 March only (middle column), and both survey dates combined (right column). Each grid cell represents a target surface roughness metric calculated using a particular statistic (x-axes) and subgrid spatial scale (y-axes). The final operations applied to aggregate the subgrid roughness metrics at the 10 m Sentinel-1 scale are the maximum (top row), mean (middle row), and minimum (bottom row). Values reported in grid cells are the average MAPE after 100 RF regression model runs. Grey cells indicate redundant model runs that were not conducted (see text).

4. Discussion

The goal of our analysis is to quantify the effect of river ice surface roughness on Sentinel-1 backscatter. We conducted aerial surveys at a site on the Yellowstone River on 19 February and 4 March 2021, representing midwinter and early spring ice conditions, respectively. To demonstrate that our dataset could successfully train an RF model, we hand-labeled areas of rubble (rough) ice and sheet (smooth) ice in orthomosaic photos of the surveyed area and trained an RF classifier to predict ice classes using Sentinel-1 backscatter data. Next, we measured surface roughness using DEMs of the surveyed area and used the measurements to create various roughness metrics, which we used as RF regression targets.

Observed density functions of surface roughness measurements from the two survey dates (Figure 5) show that the 19 February ice surface was rougher on average and spanned a wider range of roughness values than the 4 March ice surface. This was a surprising result based on our experience of hand-delineating polygons representing rubble ice and sheet ice areas in the orthomosaic photos from the two dates. Many locations in the scene that were covered with a thin layer of bright white snow in the 19 February orthophoto appeared darker in color and more textured in the 4 March orthophoto. The overall effect of the thin snow cover was that the 19 February surface appeared visually smoother than the 4 March surface. However, the SfM algorithm was able to detect ice pieces and other roughness elements in many snow-covered areas of the 19 February that were not visually apparent, but would still affect SAR backscatter. Previous ice classification studies that use a visual interpretation of aerial photos as validation data have not had the benefit of fine-scale roughness measurements to use for this type of comparison (Figure 6). If we had difficulty detecting roughness features in 0.03 m UAV orthophotos, it stands to reason that this issue may have been amplified in previous studies with lower-resolution imagery.

Figure 6 shows that the distributions of measured surface roughness within sheet ice and rubble ice samples were different between the 19 February and 4 March models. Significant overlap in measured surface roughness for sheet ice and rubble ice in the 4 March model resulted in lower classification accuracy (Figure 7). We note that increasing the area threshold value used to classify pixels increased the separation between the distributions of rubble ice and sheet ice on both dates, which should generally improve classification performance. However, for our small dataset, threshold values above 70% resulted in too few observations for the 4 March training datasets and actually reduced classification accuracy. We expect that the optimum value of this threshold parameter would change for different UAV-based datasets. Future studies using our methodology should consider adjusting this threshold value accordingly. The different roughness distributions were also consequential for regression results. The smaller range of observed roughness on 4 March translates to less spread in the 4 March regression training dataset, and therefore improved MAPE values for regression models (Figures 8 and 9).

MAPE values for spatially-based and distribution-based RF regression targets (Figure 8) suggest that Sentinel-1 backscatter may contain some information about the standard deviation of surface roughness elements within each pixel, but contains less information about the average roughness. However, a considerable spread is present in the regression results of all three variables in Figure 8. Even though MAPE values are lowest for the estimated log-normal standard deviation, the predictions for this target are so varied that they are of questionable utility. Efforts to predict spatial autocorrelation using Moran's I statistic as the regression target similarly did not produce quality results. Future studies could consider different spatial statistics, including local indicators of spatial autocorrelations [51], but any such indicators calculated at a subgrid-scale with respect to satellite SAR data should be treated with careful consideration when aggregating to a scale of the backscatter measurements.

For subgrid-statistic targets (Figure 9, plus additional figures in Supplementary Data), the wider data spread in the 19 February models (left column) compared to the 4 March models (middle column) is likely due to the different ice conditions on the two dates.

Consistently cold temperatures leading up to the 18 February 18:00 MDT Sentinel-1 image collection ensured that the thin layer of snow overlaying the ice was dry, and liquid water was not present anywhere on the ice surface. Under these conditions the bulk dielectric constant of the river ice is relatively low (i.e., permittivity is relatively high) and incident Sentinel-1 microwaves penetrate into the ice cover and are affected by the structural properties of the ice. Temperatures leading up to the 2 March 18:00 MDT Sentinel-1 image were above freezing for 12 h and hit a daytime high of 15 °C at approximately 16:00. It is very likely that liquid water was present on some areas of the ice surface at the time the 2 March image was captured. Under these wet conditions, permittivity decreases sharply and surface roughness is the dominant microwave scattering mechanism [16]. These different ice conditions could account for part of the difference in the amount of spread between the 19 February and 4 March regression models, and consequently the difference in MAPE. We note again here that the time between Sentinel-1 image collection and UAV aerial surveys was approximately 12 h for the February datasets and 36 h for the March datasets. This difference, especially during the freeze-thaw cycle of the spring transition period, is a source of error in our regression models that is difficult to quantify.

Regression models in this study performed best on targets that emphasized the minimum roughness measured within a pixel, whether that emphasis was derived from the subgrid statistic (minimum, 5th percentile) or the minimum aggregation operation. A comparison of the performance of all model configurations for a single target (Figure 9) shows that the three aggregation operations (the three rows in Figure 9) have similar amounts of relative spread in the predictions, even though the data range compresses by two orders of magnitude between the maximum and minimum aggregation operations. This is an indication that Sentinel-1 backscatter measurements may contain some information related to the minimum river ice surface roughness, which could be related to the type of microwave interactions on the ice surface (specular reflection vs. surface scattering).

We reiterate that our 0.03 m UAV surface roughness measurements do not meet the threshold criteria of 0.0056 m (i.e., $\lambda/10$) necessary to conclusively delineate radiometrically smooth and rough surfaces with respect to Sentinel-1 microwave scattering behavior. However, the upcoming NASA-ISRO NISAR satellite mission will collect L-band ($\lambda = 0.24$ m) SAR measurements on a 12-day global repeat cycle [52]. Our UAV methodology generates surface roughness measurements at the threshold 0.024 m spatial resolution simply by flying at a slightly lower altitude than the 80 m flown for this study. Using the method and calculations provided by van der Sanden and Drouin [23] and Sabins [26], and assuming an average incidence angle of 41 degrees [52] we calculate that $h < 0.0127$ m indicates a radiometrically smooth surface at the air-ice interface, $h > 0.0723$ m indicates a radiometrically rough surface, with intermediate roughness between these values. Most ice surfaces in the dataset we collected for this study would be classified as radiometrically smooth with respect to NISAR, but some rubble ice in the 19 February model would be in the intermediate roughness class. We suspect that radiometrically rough surfaces may be found in large ice jams, though that conjecture will have to be addressed by future research. We also note that our methodology is not limited to river ice and could be used to measure the roughness of any surface of interest.

5. Conclusions

We presented the first systematic, quantitative investigation of the effect of river ice surface roughness on Sentinel-1 C-band SAR backscatter. Measurements of surface roughness were derived from aerial surveys at a site on the Yellowstone River on 19 February and 4 March 2021, representing midwinter and early spring ice conditions, respectively. Our UAV-based methodology improves upon the limitations of traditional ground-based or airplane-based river ice photography, and can be used to measure ice roughness on frozen rivers globally. Poor numerical regression results (5–113% MAPE) coupled with reasonable visually-based classification results (77–96%) suggest that Sentinel-1 backscatter data contain information derived from river ice, but that information is not strongly related

to ice surface roughness. Although the results of our study are not perfectly conclusive, they suggest several relevant paths forward for future SAR-based river ice studies, which we discuss below in the context of our original hypotheses.

Our first hypothesis was that RF regression models relating river ice surface roughness to SAR backscatter are not location- or condition-specific, and that model performance will improve for models trained with data from multiple surveys. Our results based on individual-date and combined-date regression models suggest the opposite: regression error is affected by ice conditions which in turn affect Sentinel-1 backscatter, and regression models based only on surface roughness appear to work better in wet-ice conditions. However, our analysis is based on two aerial surveys which only represent a small subset of possible ice conditions on global rivers. Future work should attempt to incorporate additional survey dates to generate a larger dataset that spans a wider range of ice conditions and geographic locations. We also recommend conducting aerial surveys as close as possible to the time of satellite flyover, as permitted by weather conditions and other logistical considerations.

Our second hypothesis was that regression model performance will be affected by the spatial scale at which river ice surface roughness elements are quantified, with finer spatial scales resulting in lower regression errors. Our regression results suggest that, while model performance does generally improve for subgrid-statistic roughness targets as spatial resolution becomes finer, model performance is more strongly controlled by which tail of the distribution is emphasized by the regression target. RF regression models perform better on targets that emphasize the left tail of the distribution (minimum or 5th percentile roughness, or aggregating by minimum roughness) compared to targets that emphasize the right tail (maximum or 95th percentile roughness, or aggregating by maximum roughness). Future studies may be able to examine these patterns in more detail by incorporating fully-polarimetric SAR imagery (e.g., from RADARSAT-2) or SAR imagery at different wavelengths (e.g., L-band NISAR measurements). Adding SAR-based predictor variables derived from HH-polarized backscatter, as well as H-A- α and other polarimetric decomposition products, could improve upon results reported here and detect new trends.

Our final hypothesis was that river ice surface roughness will have at best a moderately strong correlation with Sentinel-1 backscatter because other physical ice properties are not accounted for in the regression models. Regression results using surface roughness measurements were not particularly strong, but ice classification using the traditional visually-based validation method achieved accuracies similar to those published in previous studies. This is an indication that Sentinel-1 SAR backscatter data contain information derived from the river ice, but that information is not strongly related to ice surface roughness. We suggest that the most impactful future work would include field campaigns to measure other ice properties simultaneously with surface roughness. For example, a UAV-based ground penetrating radar [53] could potentially retrieve ice thickness and structure measurements, which could be used alongside surface roughness in regression models. Spatially distributed ice core samples [23,54] could enable comparison of the relative effects of surface roughness and vertical ice structure on SAR backscatter.

Supplementary Materials: Scatter plots similar to Figure 9 for the 35 other subgrid-statistic roughness metrics are available online at <https://www.mdpi.com/article/10.3390/rs14225644/s1>.

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Data Availability Statement: All data and code used to generate results in this paper are located in the iceroughness_RF GitHub repository [48].

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Abbreviations

The following abbreviations are used in this manuscript:

CDF	Cumulative distribution function
DEM	Digital elevation model
MAPE	Mean absolute percentage error
PDF	Probability density function
SAR	Synthetic aperture radar
SfM	Structure from Motion
UAV	Uncrewed aerial vehicle

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AN INTEGRATED FIELD MEASUREMENT APPROACH REVEALS RIVER ICE
CONTROLS ON SENTINEL-1 BACKSCATTER

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An integrated field measurement approach reveals river ice controls on Sentinel-1 backscatter

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Key Points:

- GPR can be used to quantify structural properties of river ice that also influence Sentinel-1 backscatter
- VV backscatter is negatively correlated with ice thickness and VH backscatter is positively correlated with structural complexity of the ice
- More data are needed to generalize results to other rivers and ice conditions

Abstract

Warming temperatures have decreased the spatial and temporal extent of river ice globally, but have increased uncertainty surrounding ice jam flood hazard. Interpretation of satellite radar-based products for operational ice jam forecasting is complicated by ambiguity in the interactions between river ice and radar backscatter. The purpose of this study is to examine the influence of physical river ice properties on Sentinel-1 backscatter. We collected a novel field dataset of ice thickness, structure, and surface roughness and compare the in situ measurements to Sentinel-1 data using multivariate linear regression. Our analysis indicates that Sentinel-1 VV backscatter is correlated with ice thickness and VH backscatter with structural properties, but results were site-specific and showed considerable spread. While more work and data are necessary to create a generalized river ice model from Sentinel-1 measurements, ice jam forecasters can incorporate the trends shown here into the interpretation of existing radar-based river ice products.

Plain Language Summary

Ice jams on high latitude rivers bring the potential for devastating, rapid-onset floods. Although warming temperatures have decreased the spatial and temporal extent of river ice globally, there is uncertainty surrounding changing ice jam flood hazard due to increased variability in mid-winter breakup events. Ice jam forecasters use satellite-based maps to monitor river conditions, but these maps can be ambiguous with respect to the strength of river ice and its potential for jamming. The purpose of this study is to examine the influence of physical river ice properties on Sentinel-1 measurements, a particular satellite used to make river ice maps. We made field measurements of ice thickness, structure, and surface roughness and compare those data to Sentinel-1 measurements of the same ice using linear regression techniques. Our analysis provides new insight into the relationships between river ice properties and the satellite measurements, but more work is necessary to generalize our results to regional or global scales.

1 Introduction

River ice is an important component of the cryosphere that affects the water stage (Beltaos & Prowse, 2009), nutrient fluxes (Blackadar et al., 2020), and overland transportation corridors (Brown et al., 2018) associated with global high-latitude river systems. Depending on hydrodynamic and meteorological conditions, ice jams may occur during the breakup period which have the potential to cause rapid-onset localized flooding (Beltaos, 1997, 2001). Ice jam floods play important ecological (Thellman et al., 2021) and morphological (Beltaos & Burrell, 2021) roles in riparian and wetland ecosystems, but can also cause infrastructure damage totalling hundreds of millions of USD (Nafziger et al., 2021). Warming temperatures have resulted in a reduction in the extent and duration of river ice cover globally (Yang et al., 2020), but the threat of ice jam floods may actually rise in some areas due to an increase in the number and severity of mid-winter breakup events (Burrell et al., 2021; De Coste et al., 2022; Rokaya et al., 2022). Global monitoring of river ice is critical for managing and adapting to this increased variability.

Radar remote sensing, in particular synthetic aperture radar (SAR) from the C-band (5.4 GHz) RADARSAT and Sentinel-1 satellite platforms, has been used to track spatiotemporal ice formation on local to global scales. River ice can take many forms that are created through different physical processes (Beltaos, 2013b), and variations in the physical properties of these ice forms scatter incident SAR radiation in different ways (Gherboudj et al., 2010; van der Sanden et al., 2021). Previous studies have generated SAR-based ice cover maps using classifier algorithms validated using expert interpretation of aerial photos (Gauthier et al., 2006; Chu et al., 2015; Chu & Lindenschmidt, 2016), using the principle that visually rougher ice surfaces will result in a stronger SAR backscatter. Some studies (Drouin et al., June 19 - 22, 2007; Jasek et al., 2013) have reported greater than 90% classification accuracy using this qualitative process, but Palomaki and Sproles (2022) demonstrated quantitatively using uncrewed aerial vehicle (UAV)-based measurements that surface roughness at the air-ice interface is not a strong control on Sentinel-1 backscatter. Identifying the physical properties of river ice that do influence backscatter will aid in the interpretation of SAR-based ice cover maps, and ultimately provide ice jam forecasters with better information to make critical decisions.

Potential scattering-relevant river ice properties include surface roughness, thickness, and structural complexity, including the distribution of air bubbles and other impurities in the vertical ice column (Gherboudj et al., 2010). Jasek et al. (2003) and Unterschultz et al. (2009) measured ice thickness by drilling boreholes along multiple cross-channel transects on two Canadian rivers. Ice thickness and RADARSAT-1 HH backscatter were positively correlated when averaged across transects, but the relationship broke down at the individual pixel level. One complication is that ice of similar thicknesses may correspond to widely varying backscatter measurements due to differences in the structural properties (van der Sanden & Drouin, 2011). Several studies (Mermoz et al., 2013; Lindenschmidt & Li, 2018) have demonstrated correlation between fully polarimetric RADARSAT-2 products and structural ice properties, and Mermoz et al. (2013) noted that variations in ice structure were a source of error for thickness estimations derived from empirical polarimetry-based methods.

River ice thickness and structure can vary significantly over small ($\sim$ m) spatial scales due to the dynamic processes involved in ice formation (Beltaos, 2001), but most studies discussed above compared SAR data to a single borehole measurement made within a satellite pixel (8–25 m) and do not address sub-pixel spatial variability. Ground-penetrating radar (GPR) has been used to collect spatially-distributed measurements of river ice thickness and structure in several studies. Healy et al. (2007) surveyed river ice at two frequencies and showed that ice thickness measurements derived from 500 MHz GPR data showed good agreement with direct measurements. Kämäri et al. (2017) reported absolute errors of 3 cm when comparing ice thickness measurements from 800 MHz GPR data to borehole measurements. They noted that because structural properties of the vertical ice column varied significantly along GPR transects, assuming horizontally-constant permittivity (typically 3.2 for pure, cold ice) increased errors in derived ice thickness measurements. Han et al. (2023) conducted GPR surveys with 200 MHz antenna and calculated ice permittivities ranging from 3.4–4.5 depending on ice structure and sediment concentrations. Despite these numerous river ice-GPR studies, previous work has not compared GPR measurements to SAR measurements of the same river ice.

The purpose of this study is to examine the influence of physical river ice properties on Sentinel-1 SAR backscatter. Global SAR-based measurements are critical to managing the increasing variability of ice jam flood frequency and intensity, and identifying the physical properties of river ice that influence SAR backscatter will provide ice jam forecasters with better information to make critical decisions. On two field dates on the Yellowstone River in southwest Montana, USA, we collected high-resolution surface roughness measurements using UAV-based photogrammetry techniques, and ice thickness and structural measurements using a GPR and traditional borehole techniques. We compare these in situ datasets to Sentinel-1 VV and VH backscatter using single and multivariate linear regression. A deeper understanding of the relationships between river ice and Sentinel-1 backscatter will aid in the interpretation of existing SAR-based river ice products and provide guidance for future field studies.

2 Data and Methods

2.1 Study Site

Our study site was a section of ice on the Yellowstone River near Emigrant, Montana, USA (Figure 1a). The Yellowstone is the longest uncontrolled river in the continental United States (1114 km) and drains approximately 100,000 km² of the land area into the upper Missouri River. The channel at our site is approximately 90 m wide and lies just upstream of a large bend.

2.2 Sentinel-1 Data Processing

The study site lies within two descending Sentinel-1A frames (Figure 1a, inset). Sentinel-1A images over the study site were acquired on 20 and 27 February 2022 at approximately 13:34 UTC (07:34 local time). We downloaded Ground Range Detected (GRD) images from the Alaska Satellite Facility Vertex platform, then processed the images by applying an orbit file, radiometric calibration, radiometric terrain flattening, and range-doppler terrain correction to obtain VV and VH backscatter intensity in terms of γ_0 . All image processing was completed using the European Space Agency SNAP software v8.0 (European Space Agency, 2021).

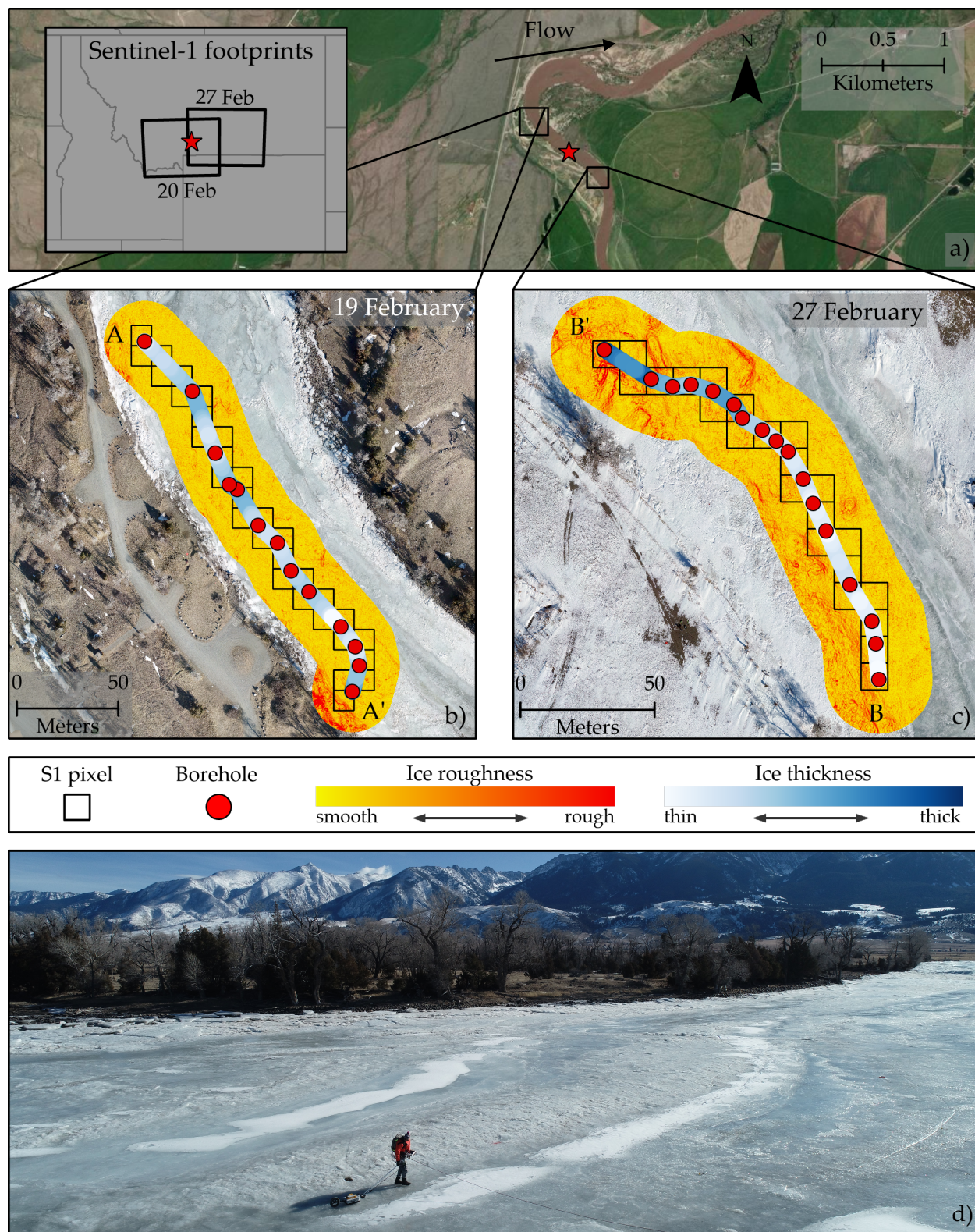


Figure 1. a) Yellowstone River field site in southwest Montana, USA with Sentinel-1 image footprints inset. b) Ice roughness, ice thickness, and borehole locations measured on 19 February. c) Same as panel b) for 27 February. d) Collecting GPR data over river ice on 19 February. Photo looking east.

2.3 Surface Roughness Measurements

Surface roughness measurements at the air-ice interface were derived from digital elevation models (DEMs) generated from UAV Structure from Motion (SfM) photogrammetry (Figures 1b and 1c). We used a commercially-available DJI Phantom 4 UAV with an integrated real time kinematics (RTK) GPS unit to fly pre-planned, gridded flight paths at 50 m above ground level with 70% front and side image overlap. We flew these missions on 19 and 27 February 2022 to coincide as closely as possible with Sentinel-1 data collection while avoiding snowy and gusty field conditions. To further reduce georeferencing error, we also surveyed six ground control points on each field date using Emlid Reach RS2 RTK GNSS receivers. SfM processing was completed using Agisoft Metashape Professional v1.6.2 (Agisoft, 2020). We followed the procedure and suggested processing parameters detailed by Over et al. (2021). DEMs generated for these surfaces had native resolutions of 0.055 m. We calculated ice surface roughness within the channel as the standard deviation of elevation within a 3×3 moving pixel window (Palomaki & Sproles, 2022), which produced roughness measurements at the native 0.055 m resolution as the DEM.

2.4 Quantification of Ice Thickness and Structure

We surveyed the river ice on both field dates using a MALÅ X3M GPR with an 800 MHz antenna. Due to safety concerns surrounding the deterioration of the ice surface, we surveyed a different reach on the second field date (Figure 1). Vertical GPR traces were collected every 0.2 m for over 165–210 m transects via a measuring wheel attached to the GPR unit. Along the transects we marked 13–15 points in the GPR software and on the ice. We surveyed the marked points with the GNSS unit, then drilled boreholes at each point and measured total ice thickness. The full GPR transects were georeferenced by interpolating GPS coordinates between borehole locations and assigning those coordinates to the traces with 0.2 m spacing.

We used ReflexW software v10.2 (Sandmeier Geophysical Research, 2022) to process the raw radargrams by adjusting the trace start time, applying dewow and bandpass filters, and computing moving averages in the along-transect direction (Figure 2). After processing we delineated the layer representing the ice-water interface, which appeared as a bright reflector due to the large permittivity discontinuity between frozen and liquid water. To calculate ice thickness across the entire transect, we first calculated GPR velocity at each borehole location (vertical red lines in Figure 2) using

$$v = \frac{T}{0.5 \cdot \text{twt}} \quad (1)$$

where T is the ice thickness measured at the borehole and twt is the two-way travel time at the ice-water interface layer. Similar to Kämäri et al. (2017) and Han et al. (2023), we observed that the structure of the ice varied along the transect, indicating that a horizontally-constant GPR velocity was not appropriate for this site. Instead, we linearly interpolated the velocities between the borehole locations, similar to interpolation of the GPS coordinates. After calculating a GPR velocity for every trace we rearranged Equation 1 to obtain continuous ice thickness measurements across the entire transect.

We also used the GPR data to quantify two structural properties of the ice. In addition to the sharp permittivity discontinuity at the ice-water interface, backscatter can also be influenced by the roughness of bottom ice surface and the presence of an air gap between the bottom of the ice and the top of the water surface (Gherboudj et al., 2008). Although we cannot separate these individual effects with our dataset, we use the GPR amplitude at the picked ice-water interface to quantify general changes at the bottom ice surface. Additionally, at every trace we calculated the integrated volume scattering within the vertical ice column (heatmaps above each transect in Figure 2). In thermally-developed, “clean” ice, very few reflectors are present within the ice column and minimal scattering of the GPR signal occurs within this volume (Gherboudj et al., 2010). On the other hand, ice covers that consist of many consolidated, refrozen ice chunks have many reflectors throughout the ice column, possibly including millimeter to decimeter scale void spaces within the vertical structure (Beltaos, 2013a). Because the GPR antenna was coupled with the ice surface during data collection, the first reflections may be representative of surface scattering at the air-ice interface instead of internal volume scattering. For this reason we delineated a second layer within the GPR data to represent the top of the vertical ice column used in volume scattering calculations. The depth of this layer was calculated at every trace as the time for the GPR wave to travel one wavelength into the ice column. Figure 2 shows that the top ice layer depth changes slightly along the transects in response to changing GPR velocity.

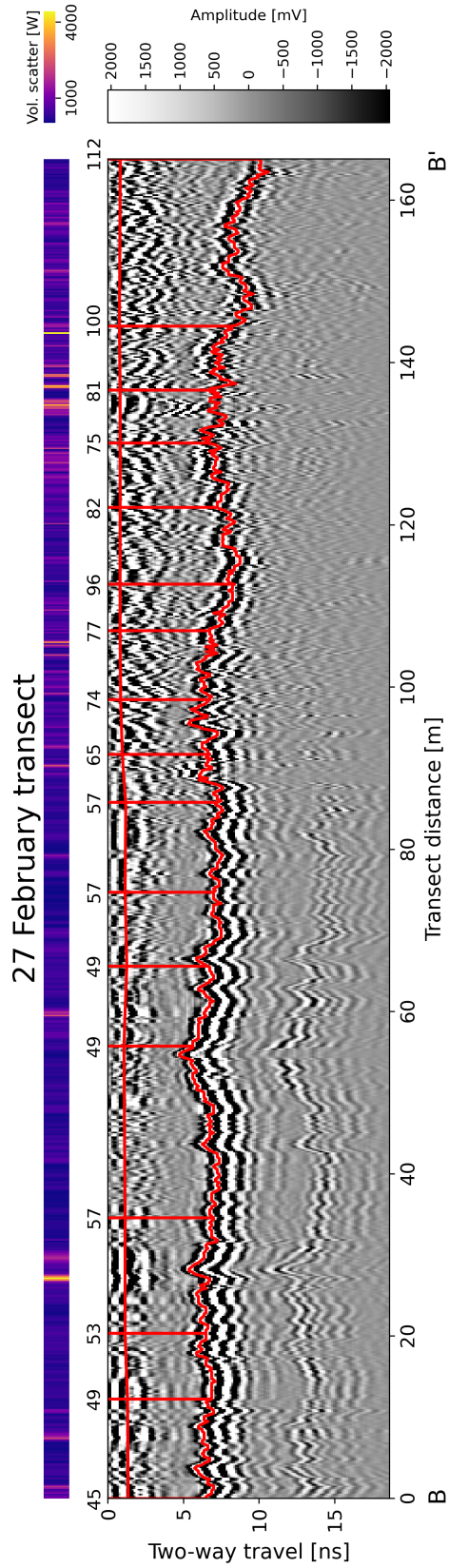
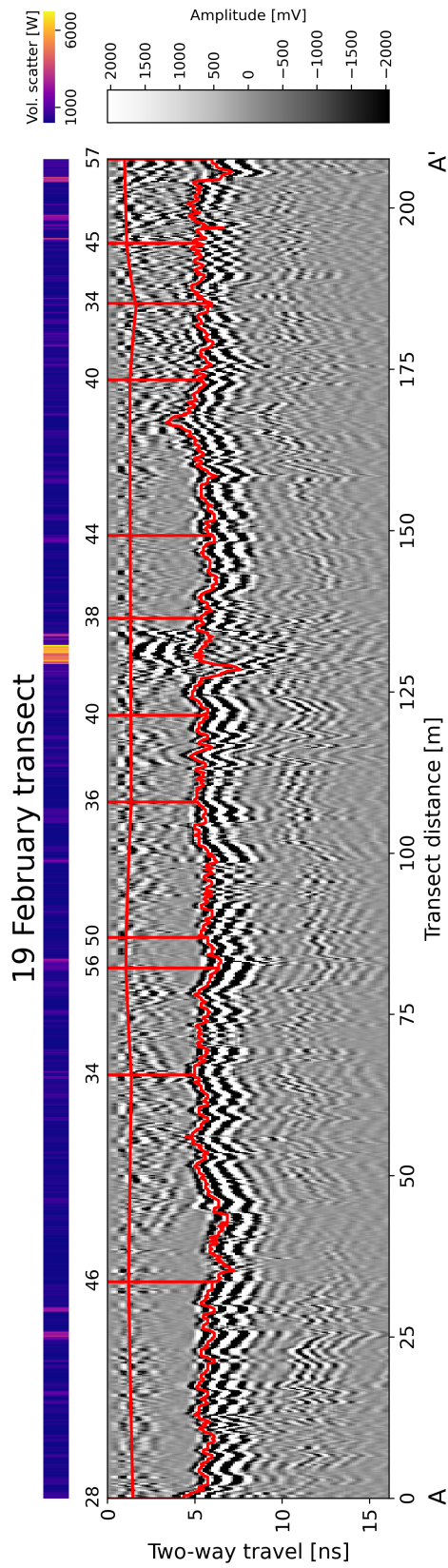


Figure 2. Processed GPR data collected on 19 and 27 February. Vertical red lines represent borehole locations, with measured ice thickness in centimeters noted above each borehole. In each transect, the lower delineated layer represents the ice-water interface and the higher delineated layer represents the upper extent of ice used for volume scattering calculations. Vertically-integrated volume backscatter between the two ice layers is shown in heatmaps above the processed GPR data.

2.5 Single and Multivariate Linear Regression

We used single and multivariate linear regression analysis to explore the relationships between the physical properties of river ice and Sentinel-1 backscatter. As shown in Figures 1b and 1c, there are many UAV- and GPR-derived ice measurements within a given Sentinel-1 pixel, so we must summarize the in situ measurements for comparison with the 10 m Sentinel-1 backscatter. We note that the number of ice roughness measurements within a Sentinel-1 pixel is constant at more than 33,000, while the number of GPR measurements within a pixel is variable and ranges from 4–64. To create the linear regression dataset we selected only the Sentinel-1 pixels that contained 10 or more GPR measurements, which provided better representation of ice conditions while maintaining a sufficiently large dataset.

We derived ice roughness variables from UAV-based surface roughness measurements using the two-step process detailed in Palomaki and Sproles (2022). Briefly, we first calculated the minimum and maximum roughness measurement within 5 m, 1 m, and 0.25 m subgrids superimposed over the 10 m Sentinel-1 pixels, then calculated the average of all subgrid measurements within each 10 m pixel. For GPR-based variables, we aggregated all GPR points within each Sentinel-1 pixel and calculated the mean, standard deviation, minimum, and maximum of the three variables (ice thickness, GPR amplitude at the ice-water interface, and total volume scattering). This resulted in 18 independent variables (six roughness, four thickness, four amplitude, and four volume scattering variables). We considered VV and VH backscatter both in units of watts and decibels for a total of four dependent Sentinel-1 variables. We had measurements covering 28 Sentinel-1 pixels from 19 February and 23 pixels from 27 February, for a total of 51 data points.

We began the regression trials with simple linear regression for all combinations of the 18 independent variables and four dependent variables. Next, we selected two categories of independent variables (e.g. amplitude and thickness) and performed multivariate linear regression for all combinations of two variables, one selected from each category (e.g. minimum amplitude and mean thickness), again running each combination on four dependent variables. We repeated this process using three and four categories of independent variables. In total, for each of the four Sentinel-1 variables, we performed 18 regressions on one independent variable, 120 regressions on two variables, 352 regressions on three variables, and 384 regressions on four variables. We examine the explanatory power of the various river ice properties using the R^2 score.

3 Results and Discussion

3.1 GPR Measurements

GPR velocities derived from borehole ice thickness measurements varied from 0.112–0.189 m ns⁻¹ along the 19 February transect, showing good agreement with results reported by Han et al. (2023). Velocities from the 27 February transect ranged from 0.137–0.239 m ns⁻¹. The upper end of this range is more typical of GPR velocities through snow than ice, and these velocities were calculated in the second half of the transect. The GPR data from 27 February (Figure 2) show a significant change between the first and second halves of the transect. The first half has relatively low volume scattering within the ice and a mirror reflection of the ice-water interface at approximately 13–15 ns. Around the 90 m mark, volume scattering increases throughout the second half of the transect and the mirror reflection disappears. While drilling boreholes on this date, we noted a considerable change in ice structure along the transect, from solid and homogeneous in the first half to heterogeneous and interspersed with air pockets in the second half. It appears that the increased structural complexity caused an increase in volume scattering, which attenuated the signal and removed the mirror reflector of the ice-water interface. These results show that GPR can be used to observe and quantify structural differences in river ice, and we hypothesize that the integrated effect of ice layers interspersed with air pockets could feasibly result in GPR velocities that approximate a snow medium.

Several velocities calculated along the 27 February transect were greater than 0.3 m ns⁻¹, i.e. faster than the speed of light. We did not use these unrealistic velocities during the interpolation process to derive ice thickness measurements. We hypothesize that there was a layer of frazil slush several tens of centimeters thick adhered to the bottom of the solid ice surface that caused these unrealistic GPR velocities. This type of ice layer has liquid water in the interstitial spaces between ice grains (Beltaos, 2013a). In a previous study, Jasek et al. (2003) found a correlation between RADARSAT-1 SAR backscatter and solid ice thickness, but noted that the total ice thickness

(which includes frazil slush) could not be measured with C-band microwaves because the incident radiation cannot penetrate the liquid water present at the ice-slush interface. Healy et al. (2007) found that their 500 MHz GPR signal was almost entirely attenuated by liquid water. We posit that our erroneous GPR velocities were a result of combining borehole measurements of total ice thickness (solid ice plus slush) with GPR travel times for solid ice only. We are unable to confirm this hypothesis because it was not possible to generate ice core samples with our ice auger. We recommend that ice cores be included in the sampling procedure for future river ice-microwave studies.

3.2 Linear Regression

Sentinel-1 VV and VH backscatter were both tested as dependent variables in units of watts and decibels. Regressions on data in watts performed better, and we present those results here. Figure 3 shows the results of the linear regression analysis for Sentinel-1 VV backscatter grouped by combinations of independent variables. Data from 27 February showed a stronger correlation with VV backscatter than did the 19 February data (Figure 3a). For the 27 February dataset, a significant jump in regression performance occurred when any ice thickness variable or the mean GPR amplitude at the ice-water interface were included in the regression models. A closer look revealed that VV backscatter has negative correlations with maximum ice thickness (Figure 3b) and ice roughness (Figure 3c), and a positive correlation with mean GPR amplitude at the ice-water interface (Figure 3d). These results are in line with theoretical river ice-microwave interactions. Thicker ice typically has more volume scatterers within its vertical structure (Gherboudj et al., 2010), and the incident wave that reaches the ice-water interface (the largest contributor to VV backscatter) is less powerful. Rougher surfaces tend to have a stronger depolarizing effect on incident SAR radiation and our results indicate that VV backscatter decreases as surface roughness increases. The positive correlation shown in Figure ??d provides evidence that the 800 MHz GPR signal and 5.4 GHz Sentinel-1 signal are sensitive to similar structural properties at the ice-water interface.

Figure 4 shows regression results for Sentinel-1 VH backscatter. Data from 19 February showed a stronger correlation with VH backscatter than did the 27 February data (Figure 4a). For the 19 February dataset, the best performing regression models were those that included the minimum GPR-derived volume scattering within the ice column. This variable has a positive correlation with VH backscatter and can explain 56% of the variance (Figure 4b). VH backscatter is also positively correlated with mean ice thickness (Figure 4c) and ice roughness (Figure 4d), where VV backscatter was negatively correlated with those variables. Previous studies that used aerial photos to visually validate SAR-based river ice maps typically report higher accuracy using co-polarized (VV or HH bands) data than cross-polarized (VH or HV) data. However, Figure 4b provides evidence that Sentinel-1 VH backscatter contains information related to structural properties of river ice which are not visible in aerial photos. We interpret the relationship shown in Figure 4b to be a minimum volume scattering threshold, where the structure of the ice must be sufficiently complex before it contains enough volume scatterers to affect Sentinel-1 VH measurements. Since the vertical structure of river ice increases in complexity as it grows thicker and stronger (Beltaos, 2013a), river forecasters may be able to use VH backscatter at a particular location to make inferences about the potential for ice jam flooding.

Our hard-earned field dataset is the result of considerable logistical planning aligning with favorable sampling conditions. However, it consists of only 51 Sentinel-1 pixels and the data show considerable spread. This is due in part to our choice to investigate backscatter measurements at the individual-pixel level, which can be noisy. Jasek et al. (2003) reported that river ice thickness and RADARSAT-1 backscatter were correlated when averaged over 500 m reaches, but this relationship broke down when the measurements were compared within individual pixels. UAV-based GPR measurements could improve upon our methodology by expanding the spatial coverage of ice measurements. Although UAV-GPR is not currently authorized in the United States, these measurements would produce a larger dataset and enable more effective noise removal from the SAR data. We also expect that a greater diversity of ice conditions would be sampled in a larger dataset, which would work toward a more generally applicable model. Figures 3a and 4a show that we cannot generalize the results from our dataset across the two field dates. We cannot definitively conclude whether these differences can be attributed to differences in the ice itself, or to differences related to the Sentinel-1 measurements. As illustrated in Figure 1a, the study site appears at different relative locations within the two Sentinel-1 images, which resulted in differences in mean incidence angle of about 10 degrees between the two field dates. We recommend that future studies make multiple measurements at the same river location to align with repeat Sentinel-1 passes over the course of a season. This would eliminate uncertainty associated with varying incidence angles.

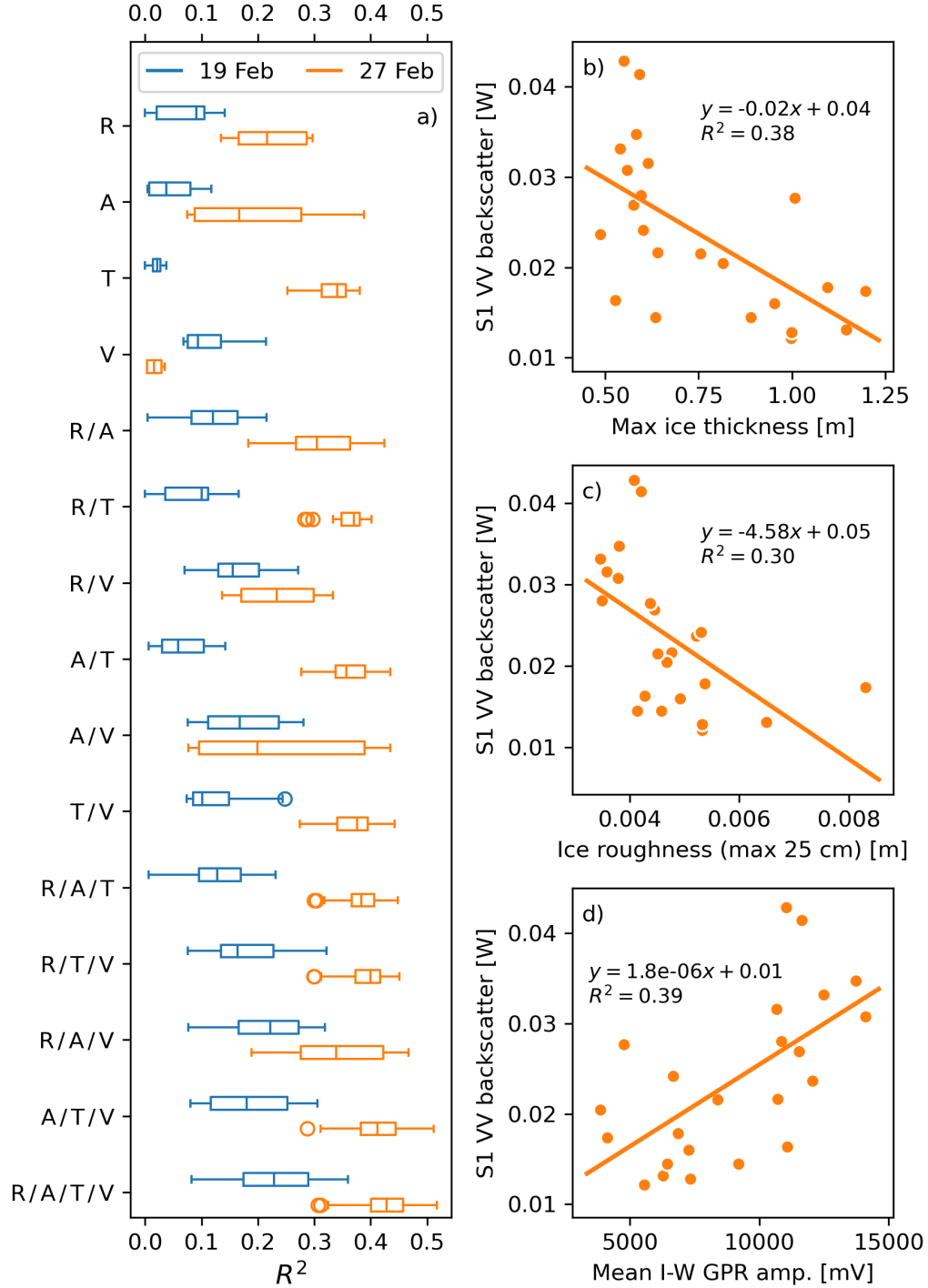


Figure 3. a) Summary of linear regression results for Sentinel-1 VV backscatter. Boxplots are grouped based on the selection of variables for regression models (R=Roughness; A=GPR amplitude at the ice-water interface; T=Ice thickness; V=GPR volume scattering). b) VV backscatter vs. maximum ice thickness. c) VV backscatter vs. mean GPR amplitude. d) VV backscatter vs ice roughness calculated with the maximum 25 cm roughness element (see text). Note orders of magnitude differences in x-axis ranges and regression slopes in panels b–d.

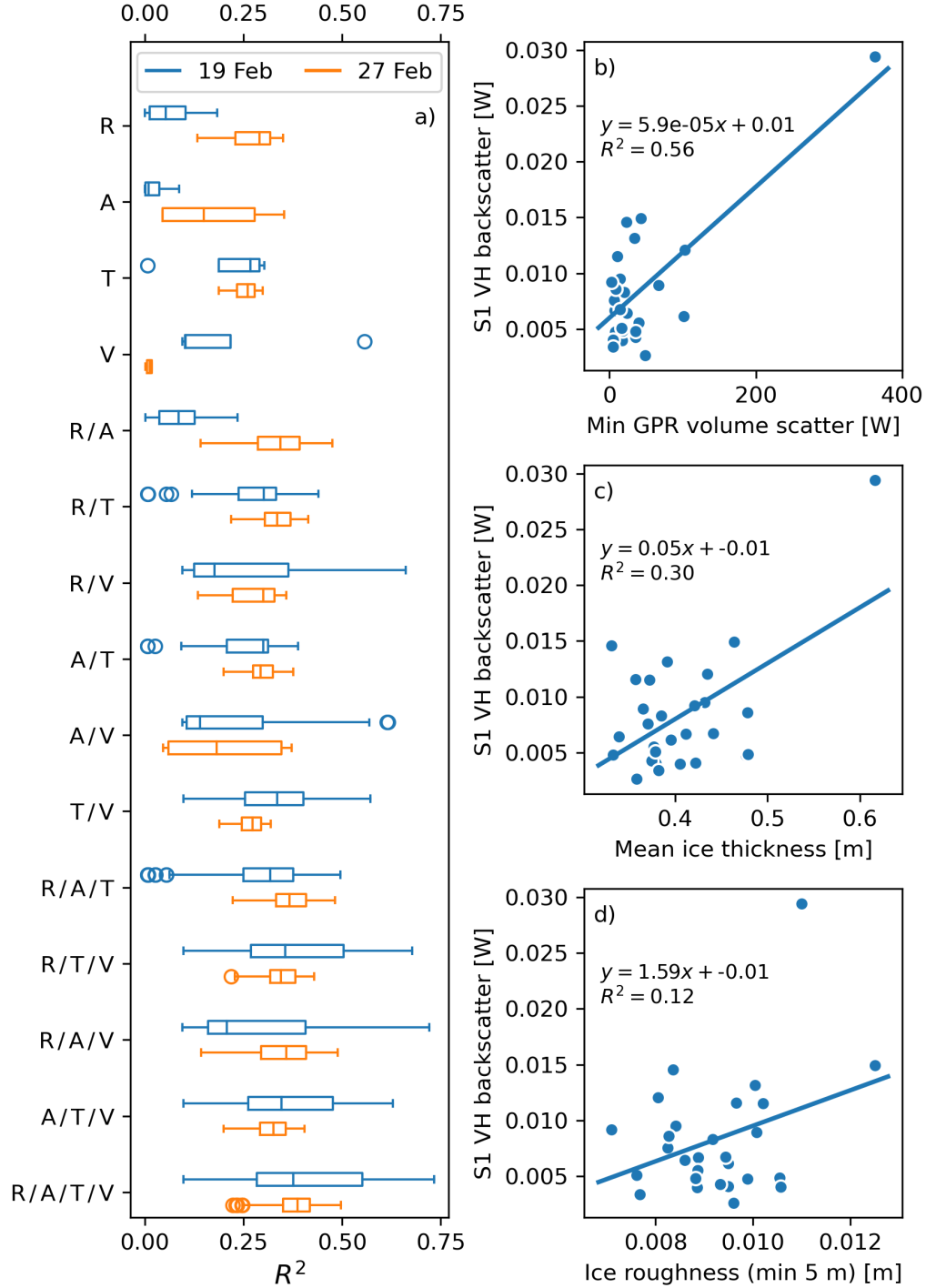


Figure 4. a) Summary of linear regression results for Sentinel-1 VH backscatter. Boxplots are grouped based on the selection of variables for regression models as in Figure 3 b) VH backscatter vs. minimum GPR volume scatter. c) VH backscatter vs. mean ice thickness. d) VH backscatter vs ice roughness calculated with the minimum 5 m roughness element (see text). Note orders of magnitude differences in x-axis ranges and regression slopes in panels b–d.

4 Conclusions

Satellite-based SAR measurements enable global monitoring of river ice conditions, which is critical to managing the increasing variability of ice jam floods in the context of our changing climate. We used UAV, GPR, and traditional borehole measurements to collect a novel dataset and systematically explored the relationship between Sentinel-1 backscatter and physical river ice properties. Results from field data align well with theoretical river ice-microwave interactions. Our data indicate that Sentinel-1 VV backscatter is correlated with ice thickness and VH backscatter contains information related to the complexity of the vertical ice column, but results were site-specific. While more work is necessary to create a generalized river ice model from Sentinel-1 measurements, ice jam forecasters can incorporate the trends shown here into the interpretation of existing SAR-based river ice products.

Acronyms

DEM Digital elevation model
GPR Ground penetrating radar
RTK Real time kinematics
S1 Sentinel-1
SfM Structure from motion
UAV Uncrewed aerial vehicle

5 Open Research

Original Sentinel-1 imagery is available from the Satellite Facility Vertex Distributed Active Archive Center. Unprocessed GPR data are available at xxx (possibly uploaded to the NSIDC). UAV photosets used to generate DEMs and surface roughness measurements are available at xxx. The processed dataset used for linear regression analysis and all code used to create the figures in this paper can be found at xxx.

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ASSESSMENT OF L-BAND INSAR SNOW ESTIMATION TECHNIQUES OVER A
SHALLOW, HETEROGENEOUS PRAIRIE SNOWPACK

Contribution of Authors and Co-Authors

Manuscript in Chapter 4

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Graphical Abstract

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Highlights

Assessment of L-band InSAR snow estimation techniques over a shallow, heterogeneous prairie snowpack

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- L-band InSAR VV phase change is sensitive to snow cover but not agricultural stubble.
- InSAR- and LiDAR-based SWE had similar spatial patterns but poor absolute agreement.
- Sub-pixel snow depth variability contributes to error in InSAR-based SWE estimates.

Assessment of L-band InSAR snow estimation techniques over a shallow, heterogeneous prairie snowpack

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Abstract

Snow water equivalent (SWE) is a critical input for weather, climate, and water resource management models at local to global scales. Despite its importance, global SWE measurements that are accurate, consistent, and at sufficiently high spatiotemporal resolutions are not currently available. L-band interferometric synthetic aperture radar (InSAR) techniques have been used to measure SWE at local to regional scales, and two upcoming L-band SAR satellite missions have renewed interest in these techniques to provide regular SWE measurements at the global scale. However, previous research demonstrating the capabilities of L-band InSAR-SWE measurement has been limited to mountain or tundra snowpack regimes. Here we examine the feasibility of applying the same techniques over a prairie snowpack, which are typically characterized by shallow snow depths (mean snow depth of 0.22 m in this study), exposed agricultural vegetation, and high spatial variability over short distances. Our study area in central Montana, USA (47.060, -109.951) was a validation site for NASA SnowEx 2021, as part of the UAVSAR snow timeseries. Airborne L-band SAR imagery was acquired

by the UAVSAR platform while concurrent snow measurements were collected using uncrewed aerial vehicle (UAV)-based LiDAR, UAV-based photogrammetry, and ground-based manual techniques. This validation dataset enables an investigation of the effects of sub-pixel snow cover heterogeneity and exposed agricultural vegetation stubble on SAR data and the resulting SWE estimations. Results based on repeated application of the Kolmogorov–Smirnov test show that UAVSAR VV phase change is sensitive to differences in snow cover but relatively unaffected by differences in agricultural stubble height. However, we did not find similarly definitive results when we used the same phase change data to estimate SWE. Although broad spatial patterns were similar in both LiDAR-derived and InSAR-derived SWE estimates, considerable differences in the two estimates were apparent in areas with large sub-pixel snow depth variability. Our results indicate that additional work is necessary to derive accurate SWE estimates in prairie environments. Regular measurements from L-band SAR satellites will provide an excellent opportunity to refine InSAR-based snow estimation techniques over shallow, heterogeneous snowpacks.

Keywords: L-band InSAR, UAVSAR, snow water equivalent, prairie snowpack

1. Introduction

Snow water equivalent (SWE), the amount of water stored in a snowpack, was identified among the most important Earth system observation targets in the 2017–2027 National Academies Decadal Survey (NASEM, 2018). Accurate global SWE measurements are critical input for water resource manage-

ment (López-Moreno et al., 2020; Siirila-Woodburn et al., 2021) and weather and climate models (Orsolini et al., 2013; Xu and Dirmeyer, 2013; Krinner et al., 2018). Despite their importance, global SWE measurements that are accurate, consistent, and at sufficiently high spatial and temporal resolutions for scientific and applied purposes are not currently available (Tsang et al., 2022). Optical and hyperspectral remote sensing techniques are well-established for measuring global snow cover extent (Rittger et al., 2013; Crumley et al., 2020), optical snow grain size (Nolin and Dozier, 2000), and snow albedo (Bair et al., 2019). However, these methods do not penetrate the snowpack and therefore cannot provide information about snow depth or SWE (Lettenmaier et al., 2015). Passive microwave measurements can be used to measure SWE on regional to global scales (Chang et al., 1987; Pulliainen, 2006; Takala et al., 2011), but the 20–25 km spatial resolution is not sufficient for all applications, and retrievals are not reliable over mountainous regions and other complex topography (Tong et al., 2010).

To overcome these limitations, synthetic aperture radar (SAR) has been employed in previous studies to derive SWE estimates using several techniques and a range of SAR frequencies. SAR is a type of active remote sensing that does not rely on solar illumination, so satellite SAR measurements can be obtained even during nighttime, polar darkness, and cloudy conditions. The spatial resolution of SAR satellite imagery is typically on the order of tens of meters, compared to tens of kilometers for passive microwave measurements. At higher frequencies (X- and Ku-band), volume scattering occurs within a snowpack as incident SAR radiation interacts with millimeter-scale snow grains and dielectric variations in the snowpack, which allows for SWE

estimation from SAR backscatter measurements (Tsang et al., 2022). A backscatter-based approach has also been employed to measure snow depth using Sentinel-1 C-band SAR measurements (Lievens et al., 2019, 2022), but the physical basis behind this technique remains an active area of investigation. At lower frequencies, dry snow is virtually transparent to incident radiation and backscatter data from a single low-frequency SAR acquisition cannot provide meaningful SWE information (Rott et al., 2003). However, the higher permittivity of snow relative to air causes a signal delay, and therefore a phase change, as the incident microwave travels through the snow medium compared to the theoretical path in a snow-free environment (Guerinussen et al., 2001). If a snow accumulation or ablation event occurs between two repeat-pass SAR acquisitions, the change in SWE (ΔSWE) can be estimated directly from the phase change using interferometric SAR (InSAR) techniques.

Ground-based experiments have demonstrated that InSAR-based SWE retrieval is not limited to low-frequency SAR instruments. For example, Leinss et al. (2015) used InSAR techniques with X- and Ku-band measurements over 4-hour temporal baselines to derive SWE with good accuracy up to 200 mm of ΔSWE . However, higher frequency measurements are susceptible to temporal decorrelation on the order of hours to days from precipitation, wind, wet snow, and air temperatures close to 0°C , while lower frequency measurements were more resilient against these decorrelation effects (Ruiz et al., 2022). In particular, Ruiz et al. (2022) concluded using tower-based measurements that L-band should be preferred over S-, C-, and X-band for satellite InSAR-based SWE retrievals because it showed the best

56 results over 6–12 day temporal baselines. C- and L-band data from airborne
 57 InSAR campaigns show similar decorrelation trends (Nagler et al., 2022; Be-
 58 linska et al., 2022). Airborne L-band data have also been collected using the
 59 UAVSAR platform (Rosen et al., 2006; Deeb et al., 2017) as part of NASA
 60 SnowEx, an ongoing multi-year, multi-sensor field campaign with the goal
 61 of addressing gaps in snow remote sensing knowledge (Durand et al., 2020).
 62 InSAR-based SWE estimates using UAVSAR data collected over sites in Col-
 63 orado (Marshall et al., 2021) and New Mexico (Tarricone et al., 2023), USA
 64 show good agreement with in situ LiDAR, ground penetrating radar, and
 65 snow pit measurements.

66 The renewed interest in L-band InSAR SWE measurements is due in part
 67 to the upcoming NASA-ISRO Synthetic Aperture Radar (NISAR, planned
 68 launch in 2024) and Radar Observing System for Europe in L-band (ROSE-L,
 69 planned launch in 2028) satellite missions. Previous studies that demonstrate
 70 satellite-based InSAR SWE retrievals primarily use C-band SAR satellite
 71 imagery. ERS-1 and ERS-Tandem InSAR pairs have been analyzed over
 72 SWE validation sites in Norway (Gunteriusen et al., 2001), the Austrian
 73 Alps (Rott et al., 2003), and the North Slope of Alaska (Li and Sturm, 2002;
 74 Deeb et al., 2011), and RADARSAT-2 timeseries have been used to estimate
 75 SWE over Arctic Canada (Eppler and Rabus, 2022; Eppler et al., 2022). Fu-
 76 ture L-band satellite missions could potentially provide more accurate SWE
 77 measurements on global scales, based on the improved InSAR coherence over
 78 longer temporal baselines.

79 The InSAR-SWE technique first presented by Guneriusen et al. (2001)
 80 assumes assumes a dry, homogeneous snowpack within a SAR pixel. Valida-

tion sites in previous studies have typically been located in alpine or tundra snow regimes where those conditions are generally satisfied, especially during mid-winter. The feasibility of the InSAR-SWE technique has not been investigated in prairie snowpack regimes, which comprise nearly 25% of seasonally snow-covered land area and have distinctly different characteristics compared to alpine or tundra snow environments (Sturm et al., 1995; Sturm and Liston, 2021). In particular, prairie snowpacks are typically shallow and highly variable over short distances. Snow cover and depth in windswept prairie environments are strongly controlled by the presence and height of vegetation (Pomeroy and Gray, 1995). Much of the land area in the Northern Great Plains (NGP) of the US and Canada is used for non-irrigated dryland agriculture (Cochran et al., 2006), and retention of seasonal snow by maintaining standing crop stubble over winter is a technique used by agricultural producers to provide an important soil moisture input for the spring planting season (Aase and Siddoway, 1980; Pomeroy and Li, 2000). Hence, snow-covered areas in the NGP often feature exposed agricultural vegetation stubble extending beyond the top of the snowpack (Harder et al., 2019), which could introduce error into InSAR-derived SWE estimates (Leinss et al., 2015). Agricultural production in the NGP is likely to become even more important in the coming decades: results using climate model projections indicate a loss of agricultural land in the US Southwest and Southern Plains due to increases in the frequency and duration of hot and dry conditions, while projected increases in minimum temperatures in NGP could result in significantly more growing degree days in this region (Matthews et al., 2018). Accurate, spatially-distributed measurements of SWE in the NGP

will be critical to support food and fiber production in these important dry-land agricultural systems.

The overarching goal of this study is to assess the feasibility of deriving L-band InSAR-based SWE estimations in a prairie environment. A secondary objective is to explore the use of InSAR techniques to identify snow presence under agricultural vegetation with varying stubble heights. Specifically, we investigate the effects of sub-pixel snow cover heterogeneity and exposed agricultural vegetation stubble on SAR data and the resulting SWE estimations. Our study area in central Montana, USA was a validation site for the NASA SnowEx 2021 field campaign. Airborne L-band SAR imagery was acquired by the UAVSAR platform while concurrent ground-based snow measurements were collected using uncrewed aerial vehicle (UAV)-based LiDAR, UAV-based photogrammetry, and manual techniques. The remainder of this paper is organized as follows: Section 2 presents the theoretical foundation for the InSAR-SWE method in more detail; Section 3 describes our dataset; Section 4 details our methodology; results are presented and discussed in Section 5; and we conclude briefly in Section 6.

2. Theoretical background

The total InSAR phase change between two repeat-pass acquisitions is the sum of the individual phase change components, including phase change caused by flat earth and topographic effects, changes in atmospheric propagation, system noise, and the two-way propagation difference between snow and the free atmosphere (Deeb et al., 2011). Guneriussen et al. (2001) denoted

129 the snow-related phase difference $\Delta\phi_s$ as

$$\Delta\phi_s = \frac{-4\pi}{\lambda} \Delta z_s \left(\cos \theta_i - \sqrt{\varepsilon - \sin^2 \theta_i} \right) \quad (1)$$

130 where λ is the SAR wavelength, Δz_s is the change in snow depth, θ_i is the
 131 incidence angle, and ε is the bulk snowpack permittivity (see also Figure
 132 7 in Leinss et al. (2015)). Spatially distributed field measurements of snow
 133 permittivity are difficult to acquire, but for dry snow the complex component
 134 of permittivity ε'' is negligible compared to the real component ε' , which
 135 can be approximated from bulk snow density ρ_s alone using (Mätzler, 1996;
 136 Wiesmann and Mätzler, 1999)

$$\varepsilon' \approx 1 + 1.6\rho_s + 1.8\rho_s^3 \quad (2)$$

137 Substituting (2) into (1) and solving for Δz_s gives

$$\Delta z_s = -\frac{\Delta\phi_s \lambda}{4\pi} \left(\cos \theta_i - \sqrt{(1 + 1.6\rho_s + 1.8\rho_s^3) - \sin^2 \theta_i} \right)^{-1} \quad (3)$$

138 This form of the InSAR-SWE relationship has been used by many previous
 139 studies. Leinss et al. (2015) later showed that the density-dependent term
 140 $\xi(\theta_i, \rho_s) = \cos \theta_i - \sqrt{\varepsilon - \sin^2 \theta_i}$ in (1) is nearly linearly related to ρ_s over a
 141 wide range of incidence angles and can be approximated by

$$\xi(\theta_i, \rho_s) \approx -\frac{\alpha}{2} \left(1.59 + \theta_i^{5/2} \right) \cdot \frac{\rho_s}{\rho_w} \quad (4)$$

142 where α is a correction factor, ρ_w is the density of water, and the fac-
 143 tor 1.59 was determined empirically. Substituting (4) into (1) and using
 144 $\Delta\text{SWE} = \Delta z_s \rho_s / \rho_w$ gives

$$\Delta\phi_s = \frac{4\pi}{\lambda} \cdot \frac{\alpha}{2} \left(1.59 + \theta_i^{5/2} \right) \cdot \Delta\text{SWE} \quad (5)$$

145 which is a linear relationship between InSAR phase change and SWE for
 146 a fixed incidence angle. Equation (5) can be inverted to solve for ΔSWE
 147 directly as

$$\Delta\text{SWE} = \Delta\phi_s \cdot \frac{\lambda}{2\pi\alpha} \left(1.59 + \theta_i^{5/2}\right)^{-1} \quad (6)$$

148 The optimal correction factor α_{opt} in (6) depends on incidence angle and
 149 snow density but falls between 0.95–1.05 for a wide range of angles and densi-
 150 ties (Leinss et al., 2015, their Figure 9). For snow densities below 400 kg m^{-3} ,
 151 using the appropriate $\alpha = \alpha_{\text{opt}}$ in (6) results in a root-mean-square error of
 152 less than 7% for all incidence angles compared to the exact solution given by
 153 (1). Even with the additional error, (6) may be particularly well-suited for
 154 use with satellite data at regional and global scales because it does not require
 155 snow density as an input to estimate SWE. We use (6) to derive InSAR-based
 156 SWE estimates over the spatially heterogeneous prairie snowpack at our field
 157 site.

158 3. Study site and datasets

159 Our study site is a 1 km^2 region within Montana State University’s Cen-
 160 tral Agricultural Research Center (CARC) centered at (47.060, -109.951)
 161 near Moccasin, MT (Figure 1a). The site sits between 1288–1298 m eleva-
 162 tion and features flat terrain subdivided into fields that are used for agronomy
 163 experiments. Soils across the site consist primarily of well-drained, shallow
 164 ($\sim 30\text{cm}$) Danvers–Judith clay loams with a bulk density of 1.425 g cm^{-3} . In
 165 preparation for several planned SnowEx intensive observation periods (IOPs)
 166 during the 2020–2021 winter season, we installed an instrumentation net-
 167 work at the CARC that includes a main weather station, nine soil tempera-

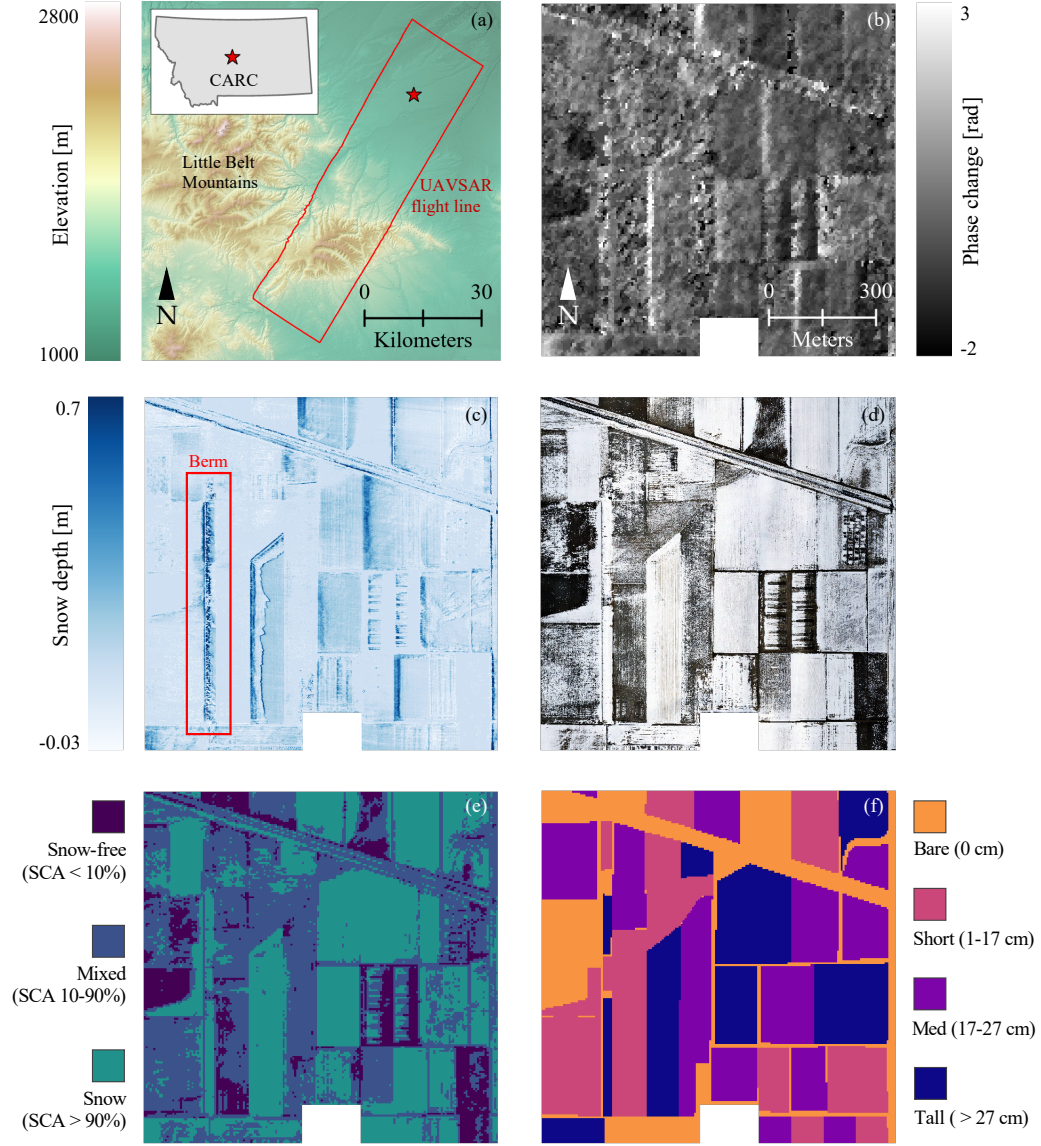


Figure 1: (a) Site overview map showing the location of the CARC within the UAVSAR flight line. (b) InSAR phase change (January 15–20 pair) within the CARC study site at 5.33 m spatial resolution. (c) LiDAR-derived snow depth measurements from 21 January at 30 cm spatial resolution. The berm feature which formed on a leeward side of the natural windbreak is marked by the red box. (d) True-color orthomosaic photo from 21 January at 10 cm spatial resolution. (e) Snow cover classes within the study site at 5.33 m spatial resolution. (f) Stubble classes within the study site at 5.33 m spatial resolution. Panels (c)-(f) have the same spatial extent and scale as Panel (b).

ture/moisture stations, and a cosmic ray neutron sensor (Figure A.13). The first SnowEx IOP at the CARC occurred between 15 and 21 January 2021. On 15 January the site was completely snow-free except for a dense berm feature that formed on the leeward side of a natural wind break (~ 2 m tall shrub vegetation) during early-season snow events. A small snow event occurred on 18 January. Persistent cold temperatures inhibited melting of the newly-deposited, shallow snowpack but high winds during and after the event caused sublimation and wind transport over a period of several days. IOP operations at the CARC were scheduled concurrently with UAVSAR flights and included UAV-based LiDAR and photogrammetry flights, snow pit observations, and manually-probed snow depth measurements. The first IOP was completed by the end of the day on 21 January.

UAVSAR data were acquired over the CARC and the surrounding region (Figure 1a) from an altitude of 12.5 km on 15 and 20 January, representing snow-free and snowy conditions, respectively. During data acquisition, the UAVSAR platform transmits microwaves and detects backscattered radiation in both horizontal (H) and vertical (V) polarizations. These individual channels are combined to create a quad-pol dataset for each acquisition consisting of HH, HV, VH, and VV bands, where the first letter indicates the transmitted polarization and the second letter indicates received polarization. An interferogram created from the two acquisitions provides amplitude, phase change, and coherence data for all four polarizations at 5.33 m spatial resolution (Figure 1b). Data were collected at a central frequency of 1.26 GHz with a bandwidth of 80 MHz. The full annotation file with all interferogram processing parameters is available in the Supplemental Material. Although phase

193 change from any polarization can be used in (6), previous studies typically
 194 use co-polarizations HH or VV because of higher radar coherence compared
 195 to the cross-polarizations. We detail our polarization selection process in
 196 Section 4.1.

197 To validate the UAVSAR-based SWE estimates, we collected spatially
 198 distributed snow depth measurements using a UAV-mounted Phoenix Sys-
 199 tems Ranger LR LiDAR unit. Data for a base model were collected in snow-
 200 free conditions on 15 January using a 1550 nm wavelength laser. UAV oper-
 201 ations planned for 20 January were postponed due to strong winds and gusty
 202 conditions near the surface. Snow-on data were captured on 21 January us-
 203 ing a 905 nm wavelength laser. Snow depth measurements for 21 January
 204 were calculated by subtracting the snow-free model from the snow-on model
 205 (Figure 1c). The north–south running berm feature is marked with the red
 206 box.

207 We also surveyed the site on 21 January using a Vision Aerial Switchblade-
 208 Elite UAV equipped with a real-time-kinematics GPS unit and a Sony α 6000
 209 24.3 megapixel camera. The boundaries of the fields for the different crop
 210 types are apparent in the orthomosaic photo of the site (Figure 1d). We
 211 applied a binary random forest image classifier to the orthomosaic photo to
 212 generate a snow presence dataset at the original 10 cm spatial resolution.
 213 For analysis, snow presence data were averaged inside each 5.33 m UAVSAR
 214 pixel to derive fractional snow covered area (fSCA) ranging from 0–100%.
 215 We then classified the continuous fSCA data at UAVSAR resolution using
 216 three labels (Figure 1e): snow-free (fSCA < 10%), mixed (fSCA 10–90%),
 217 and snow (fSCA > 90%). We note that although we could have used this

high-quality photoset to derive snow depths based on Structure-from-Motion (SfM), UAV-based LiDAR has less error associated with snow depth retrieval than UAV-SfM in a prairie agricultural environment (Harder et al., 2020).

Vegetation presence and height are strong controls on snow presence and depth across the different fields within the open, windy study area (Pomeroy and Gray, 1995). At the end of the growing season the crops within the site were harvested using techniques that left vegetation stubble of different heights in different fields. Stubble heights ranged from 0 cm (bare ground, including fields with no stubble after harvest and also dirt roads within the site) to 61 cm. Stubble heights were uniform within the boundaries of a given field, and the specific heights were selected for their relevance to the agronomy experiments conducted at the study site (i.e. not systematically distributed for the purposes of the current study). For our analysis we classified the stubble using four labels (Figure 1f): bare ground (0 cm), short stubble (1–17 cm), medium stubble (17–27 cm), and tall stubble (> 27 cm). These boundaries were selected to divide the pixels with stubble into three classes with approximately equal sample sizes.

Additionally, we collected traditional snow pit measurements and spatially distributed probed snow depth measurements. On 20 January the only location in the scene where snow depth was sufficiently deep to dig snow pits was along the dense berm feature. We dug two snow pits in locations along this feature, which provide the only in situ snow density measurements in our dataset. However, the snowpack that comprised the berm feature on 20 January contained several layers of months-old snow and was therefore not representative of the scene as a whole, which was largely snow-free before

the snow event on 18 January. In order to obtain a scene-wide snow density estimate from the two snow pits we consider only the density measured in the top 10 cm of snow, a wind slab with small snow grains (< 1 mm). Mean snow density calculated from four density measurements (400, 330, 360, and 320 kg m^{-3}) in this layer across the two snow pits was 352 kg m^{-3} (35.2%). We did not collect liquid water content measurements in the snow pits, but temperature profiles from both pits indicate below-freezing temperatures. We assume that snow is dry across the study site. We use the probed snow depth measurements taken on 21 January to validate the LiDAR-derived snow depth measurements (see measurement locations in Figure A.13). Mean probed snow depth across the site, including measurements taken within the berm feature, was 0.22 m.

Figure 2 shows photos taken at the field site on 21 January which illustrate the nature of the shallow, spatially variable snowpack and complex snow-vegetation interactions.

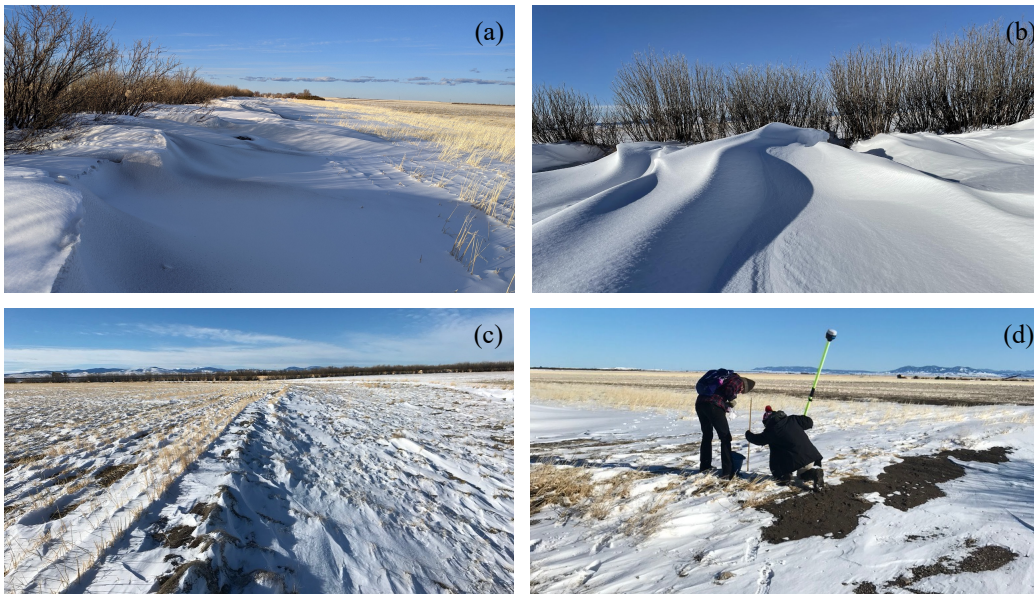


Figure 2: Photos of the field site taken on 21 January. Rows of agricultural stubble are spaced 30 cm apart. (a) Looking north along the berm feature, which formed on the east side of the natural vegetation wind break. (b) A close-up of the spatial variability within a small section of the berm. (c) Looking west toward the wind break and berm. (d) Collecting snow depth measurements along a transect in the shallow snowpack. See Figure A.13 for transect locations.

258 4. Methods

259 4.1. Polarization selection and zero-phase calibration

260 The InSAR-SWE technique is valid for phase change from any polariza-
 261 tion. We select a polarization to use based on coherence, a dimensionless
 262 measure of the similarity of phases and amplitudes of two radar echoes. Co-
 263 herence γ ranges from 0–1 and can be calculated for each polarization at each
 264 pixel as (Rosen et al., 2000)

$$\gamma = \frac{\langle s_1 s_2^* \rangle}{\sqrt{\langle s_1 s_1^* \rangle \langle s_2 s_2^* \rangle}} \quad (7)$$

265 where s_i is the complex signal (containing both phase and amplitude infor-
 266 mation) from the i th SAR image, $*$ denotes the complex conjugate operation,
 267 and angled brackets denote averaging over a spatial window (3×12 pixels in
 268 the range $\times$ azimuth directions for our UAVSAR interferogram). Low coher-
 269 ence values indicate that the two signals retrieved from the same location at
 270 different times do not represent similar scattering interactions, suggesting a
 271 significant change in the surface characteristics (Ulaby et al., 2014). In snow-
 272 related InSAR studies, significant drops in coherence can be interpreted as a
 273 transition from dry to wet snow in that location (Strozzi et al., 1999; Leinss
 274 et al., 2015), or influence from wind redistribution of recent snow (Ruiz et al.,
 275 2022).

276 Figure 3 shows histograms of scene-wide coherence for the four UAVSAR
 277 polarizations. Histogram bars are colored by snow cover class. The VV po-
 278 larization has the highest coherence, with median coherence of 0.66 compared
 279 to 0.51 for the HH polarization. We speculate that this difference may be due
 280 to the structure of the agricultural vegetation in the study site. Individual

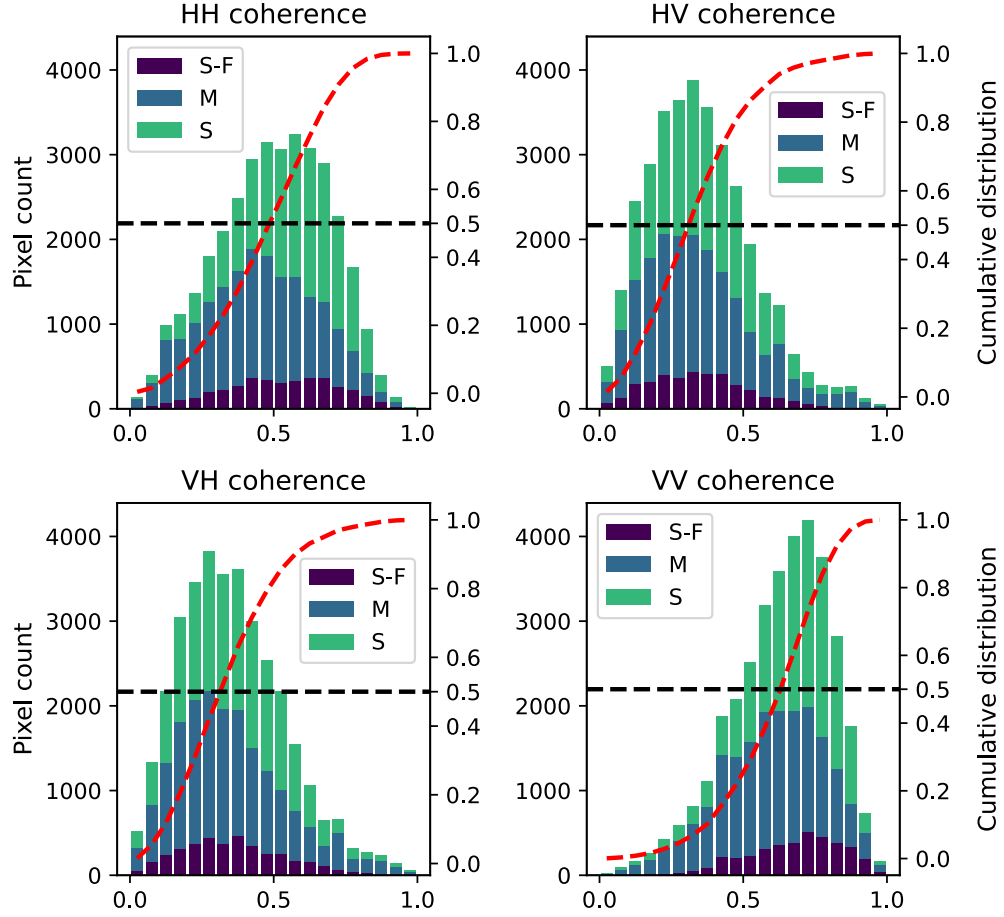


Figure 3: Coherence of the four UAVSAR polarizations. Histogram bars representing pixel counts are binned in intervals of 0.05 and colored by snow cover class (S-F=Snow-free; M=Mixed; S=Snow). Red dashed lines represent cumulative distributions of coherence calculated using all pixels. Horizontal black dashed lines mark 50% cumulative distribution to aid in visual identification of median coherence for each polarization.

281 pieces of stubble have diameters on the order of a millimeter or less, and
 282 there is a 30 cm gap between adjacent rows. This physical layout is more
 283 conducive to depolarizing horizontal waves than vertical waves. Similar to
 284 previous studies, coherence was higher for co-polarized than cross-polarized
 285 data. Median coherence was 0.33 for both HV and VH polarizations. Based
 286 on these results we select the VV phase change data as the basis for our SWE
 287 measurements.

288 Previous InSAR studies have handled low coherence in different ways.
 289 Guneriussen et al. (2001) and Li and Sturm (2002) applied the InSAR-SWE
 290 algorithm over their entire study sites regardless of coherence, but noted
 291 increased uncertainties around coherence values below 0.2 and 0.25, respec-
 292 tively. In their season-long timeseries study, Leinss et al. (2015) discarded
 293 acquisition pairs when scene-wide coherence was below 0.5. A similar tech-
 294 nique has been used in subsidence-focused studies with UAVSAR data, but
 295 with a coherence threshold of 0.21 (Bekaert et al., 2019). Another method is
 296 to use a coherence threshold to mask out individual pixels, which still allows
 297 for analysis of high-quality interferometric data in an image that may also
 298 have some low-quality areas (Jones et al., 2016). We adopt this pixel-based
 299 method to apply over our single interferogram. Because our study is a test
 300 of the InSAR-SWE technique in prairie environment with complex snowpack
 301 characteristics, we choose a relatively conservative coherence threshold of
 302 0.5 to minimize the possibility that low-quality SAR data would affect our
 303 analysis and results.

304 The left panel of Figure 4 shows the percentage of pixels below this coher-
 305 ence threshold based on different combinations of stubble height and fSCA.

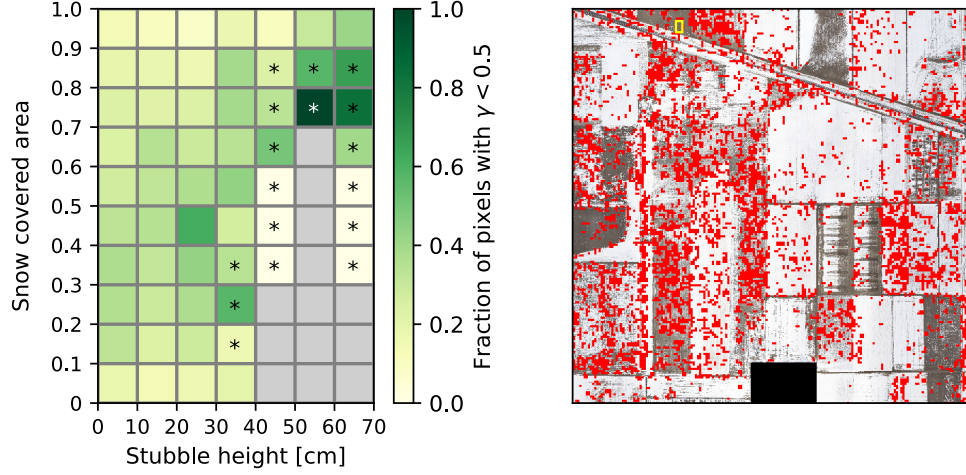


Figure 4: (left) Heatmap showing percentages of pixels masked out using the coherence threshold of 0.5, separated by different combinations of stubble height and fSCA. Gray squares in the heatmap mark combinations that do not represent any pixels in the real dataset. Asterisks mark combinations that contain fewer than 30 pixels across the scene. (right) Locations of UAVSAR pixels with VV coherence lower than the threshold value of 0.5 (marked in red), which represent 21.5% of the scene. The 4×3 pixel grid used for phase calibration is notated with a yellow box in the northwest portion of the site. Background image is the orthophoto collected on 21 January.

306 Although some combinations lead to very high (e.g. stubble between 50–
 307 60 cm and fSCA between 0.7–0.8) or very low (e.g. stubble between 40–50
 308 cm and fSCA between 0.3–0.4) percentages of masked pixels, these combi-
 309 nations have fewer than 30 pixels across the entire scene and it is difficult
 310 to draw broad conclusions with these small sample sizes. In general, this
 311 heatmap shows that the full range of fSCA and stubble height across the
 312 scene are represented in the unmasked, high-coherence dataset. It also gives
 313 an indication that the vast majority of pixels with stubble taller than 40 cm

are fully snow-covered. The right panel of Figure 4 shows that the 7459 pixels (21.5% of the scene) masked using the coherence threshold do not display any obvious spatial patterns. Many of the pixels that overlap the natural vegetation windbreak are masked out using this threshold, but most of the pixels over the heterogeneous berm just east of the windbreak maintain coherence above 0.5. This indicates that L-band SAR has the potential to retrieve reliable data even over a snowpack with depths that are spatially variable at the sub-pixel scale. The remaining high-quality pixels after masking had an average coherence of 0.70.

Prior to applying Equation (6) it is necessary to calibrate the InSAR phase, a process which requires a location in the scene with known changes in surface characteristics. For this study we identified a 4×3 grid of UAVSAR pixels (Figure 4), the largest contiguous area with coherence greater than 0.5 for all pixels, no vegetation stubble, and no snow cover on 21 January. Mean coherence for these pixels was 0.8 and minimum coherence was 0.61. Changes in soil moisture can also modulate InSAR phase (De Zan et al., 2014). Volumetric water content (VWC) measurements from a nearby soil moisture station show very small changes between the times of the two acquisitions (Figure A.14c): VWC increased by 0.8 percentage points (pp) at 5 cm depth, increased by 0.6 pp at 10 cm depth, and decreased by 0.6 pp at 20 cm depth. We also note that the soil at this station was frozen at 5, 10 and 20 cm depth for the entire period between 15 and 21 January (Figure A.14d). Therefore we expect negligible phase change due to changing soil moisture conditions. After accounting for effects from snow, vegetation, and soil moisture, we can attribute any phase change to the combined effects of atmospheric delay and

339 system noise. Mean VV phase change in the 4×3 pixel group was -0.069
 340 radians. We added 0.069 radians to all pixels in the scene before proceeding
 341 with analysis, under the assumption that atmospheric effects are constant
 342 over our 1 km^2 scene and that systematic error is normally distributed. We
 343 note that the phase calibration could be made more robust by incorporating
 344 a larger pixel group (Bamler and Hartl, 1998), but this group of 12 pixels
 345 was the best sample for our study site with its complex snow distribution.

346 4.2. Kolmogorov-Smirnov (K-S) test

347 Our dataset allows us to investigate the effects of snow cover and stubble
 348 height on UAVSAR phase change, both separately and together. For this
 349 analysis we select the two-sample Kolmogorov-Smirnov (K-S) test, a non-
 350 parametric statistical test that can be used to answer the question: What is
 351 the probability that two samples were drawn from the same underlying dis-
 352 tribution? The one-sample K-S test is often used as a goodness-of-fit test to
 353 compare sample data to a known probability distribution function. While the
 354 two-sample version does not provide any information about the theoretical
 355 underlying distribution (e.g. assumptions of particular distribution functions,
 356 or quantifying scale or shape parameters), we use it here to examine whether
 357 statistical differences exist between distributions of UAVSAR phase change
 358 over groups of pixels with different stubble and snow cover characteristics.
 359 For example, we can first select only pixels that have tall stubble, and then
 360 further subset into snow-free, mixed, and snow pixels. Distributions of phase
 361 change for the three pixel groups can be compared in a pairwise manner with
 362 the K-S test. We can repeat this analysis for all combinations of snow cover
 363 and stubble height. Significant differences (or lack thereof) between distri-

364 butions may indicate how the phase change is affected (or not) by snow and
 365 vegetation.

366 Like other statistical tests, the K–S test calculates both a test statistic
 367 and an associated p -value. Since we wish to investigate statistical differences
 368 between distributions, we will draw conclusions based on the p -value. In our
 369 dataset, most pixel groups (e.g. snowy pixels with tall stubble) contain several
 370 thousand pixels. Calculation of any p -value depends on sample size and
 371 large samples can artificially decrease the p -value, indicating a statistically
 372 significant relationship when one does not actually exist (Lin et al., 2013). To
 373 counter this problem we randomly sample 100 pixels from each pixel group
 374 and apply the K–S test to the samples. We repeat this process 100 times
 375 to avoid sample bias. We choose $c = 0.001$ as our critical value; however,
 376 multiple statistical comparisons require an adjustment to the critical value at
 377 which the null hypothesis is accepted or rejected (Rice, 2007). We apply the
 378 Bonferroni correction by dividing the critical value by the number of tests,
 379 and run each of the 100 K–S tests with $c = 10^{-5}$ as the critical value.

380 4.3. *InSAR SWE estimation*

381 Equation (6) is sensitive to SAR incidence angle, which is determined by
 382 the orientation of the sensor and the local topography. The calculation of
 383 incidence angle, and therefore estimated SWE, is affected by the accuracy of
 384 the underlying digital elevation model (DEM) used to represent the terrain
 385 in the scene. Typically, the incidence angles for UAVSAR scenes are cal-
 386 culated using a downsampled Shuttle Radar Topography Mission (SRTM)
 387 DEM, which was originally created from C-band single-pass SAR data ac-
 388 quired in February 2000 by the SIR-C instrument. During this acquisition

389 period the likely presence of snow over much of North America, possibly with
 390 varying amounts of liquid water in different locations, introduces potential
 391 error in the DEM (Tarricone et al., 2023). We observed artifacts in the
 392 SRTM-based DEM over our study site that rendered the data unsuitable for
 393 SWE estimation. We did not use this DEM in our InSAR-SWE estimates,
 394 and instead created a local incidence angle map based on a 30 cm LiDAR-
 395 derived DEM acquired at the site on 15 January in snow-free conditions and
 396 upsampled to 5.33 m resolution. Calculations for incidence angle using the
 397 original UAVSAR path length vector data and our high-resolution DEM were
 398 completed with the `uavsar_pytools` Python package (Keskinen et al., 2022).

399 Validation data for InSAR-SWE estimates are derived using LiDAR snow
 400 depth measurements, which required some post-processing. First, we calcu-
 401 lated the snow-off bias with the original dataset at 30 cm resolution. Since
 402 exposed agricultural stubble can introduce additional error into lidar mea-
 403 surements (Harder et al., 2020), we calculated scene-wide snow-off bias using
 404 only vegetation-free pixels. Total bias for these 476,634 pixels was -1.746
 405 cm. We added 1.746 cm to all lidar pixels in the scene. Next, we multi-
 406 plied bias-adjusted lidar snow depths by fSCA, calculated at the same 30 cm
 407 resolution. This step sets all lidar pixels with 0 fSCA to 0 cm snow depth.
 408 Finally, we upsampled the lidar snow depth measurements to UAVSAR res-
 409 olution by averaging all bias-adjusted, SCA-weighted lidar measurements
 410 within each UAVSAR pixel. LiDAR-based SWE was derived by multiply-
 411 ing the upsampled snow depth measurements by estimated scene-wide snow
 412 density of 352 kg m^{-3} , which was derived from snow pit measurements (Sec-
 413 tion 3). LiDAR snow depth data were separately validated using probed

414 measurements.

415 5. Results and discussion

416 5.1. *K-S analysis*

417 Figure 5a shows the size of UAVSAR pixel groups based on 21 January
 418 snow cover and stubble classes that we use for the K-S analysis. As ex-
 419 pected for prairie environments, 99% of pixels that contain tall stubble also
 420 have some amount of snow cover (‘mixed’ or ‘snow’ snow cover classes).
 421 However, the relationship between snow and stubble height is not perfectly
 422 correlated. For example, bare pixels (0 cm stubble) account for nearly 25% of
 423 the scene, and 80% of these pixels also contain some amount of snow cover.
 424 Figure 5b shows that snow depth generally increases with stubble height,
 425 though considerable spread is evident in taller stubble.

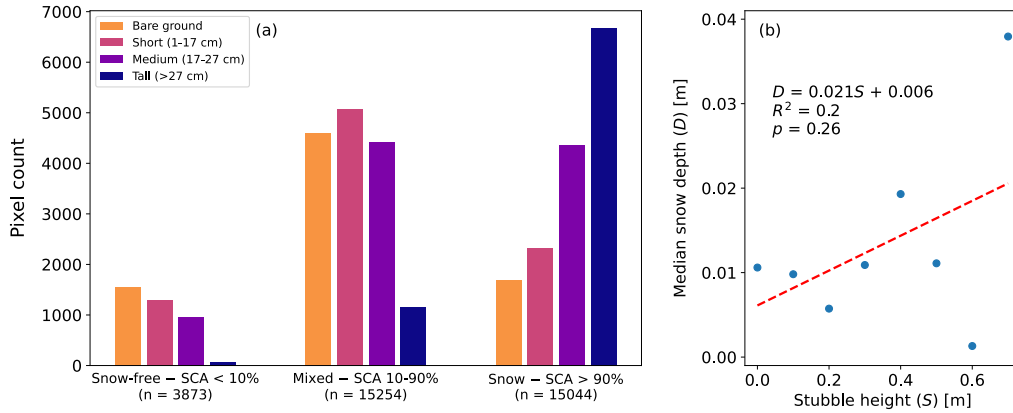


Figure 5: (a) Size of UAVSAR pixel groups based on 21 January snow cover and stubble classes used in K-S analysis. (b) Median snow depth calculated for 10 cm stubble height bins.

426 The left column of Figure 6 shows cumulative distributions of UAVSAR
 427 VV phase change for the three snow cover classes grouped by the four stubble
 428 classes. Grouping pixels in this way allows us to examine differences in phase
 429 change related to snow cover independent of vegetation effects. The right
 430 column of Figure 6 shows the results of the pairwise K-S analysis, where the
 431 grid cells indicate the number of statistically significant K-S tests (out of
 432 100) for a given pair of phase change distributions. We note that one pixel
 433 group, snow-free pixels with tall stubble, had only 62 pixels. For all K-S tests
 434 involving that pixel group, we randomly sampled 62 pixels from the second
 435 group and compared the sample to the entire 62-pixel set of snow-free pixels
 436 with tall stubble. All other tests were conducted using a random sample of
 437 100 pixels from the both distributions up for comparison.

438 In every instance where the K-S test compared two samples drawn from
 439 the same pixel group, test results did not indicate evidence of significantly
 440 different distributions (i.e. the diagonals of the K-S result tables in Figure 6
 441 are all 0). These results are equivalent to zero observed Type II error, in-
 442 dicating high statistical power of our repeat-testing method. On the other
 443 hand, K-S analysis for samples drawn from different pixel groups often in-
 444 dicated statistical differences between distributions. For all stubble classes,
 445 phase change distributions from snow-free pixels were almost always signif-
 446 icantly different when compared to phase change distributions from pixels
 447 with any snow ('mixed' and 'snow' classes). K-S tests comparing mixed and
 448 snow pixels displayed more variation between stubble classes: phase change
 449 distributions between mixed and snow pixels were significantly different in
 450 about half of the tests within short stubble pixels, about a quarter of the

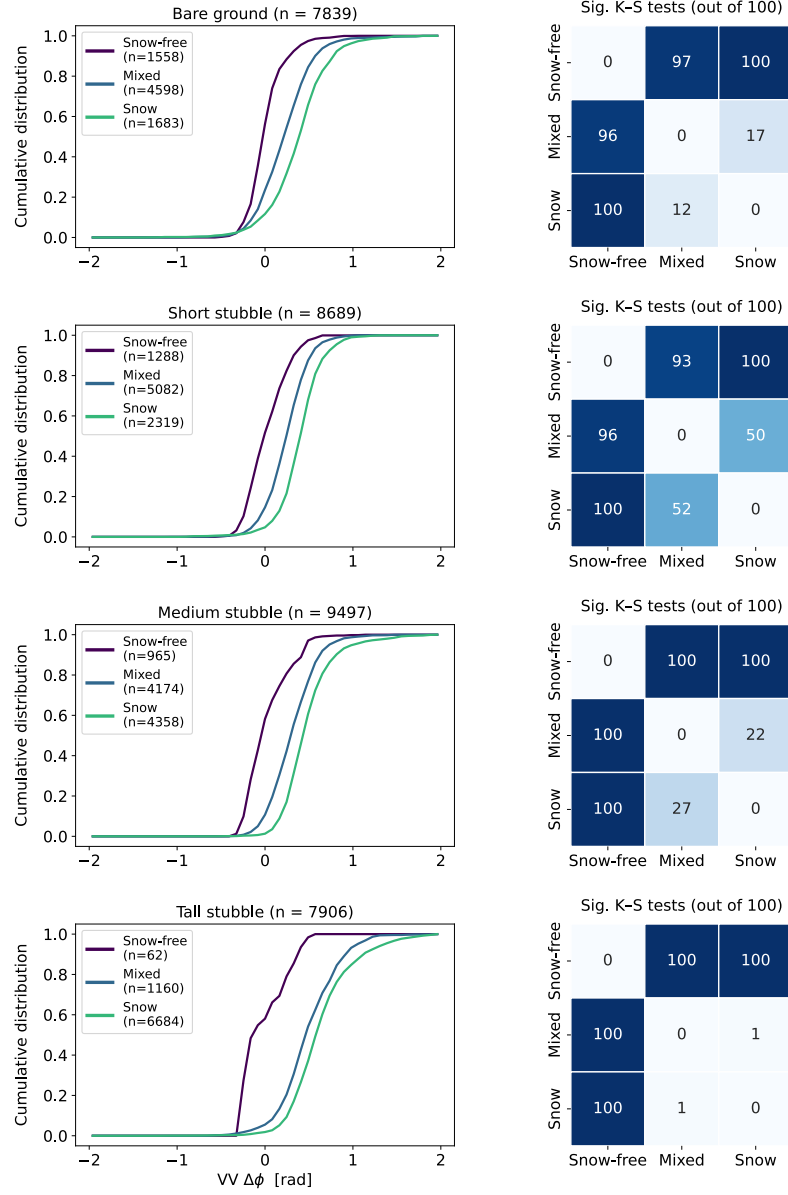


Figure 6: Cumulative distributions of VV phase change for the three snow cover classes (left column), grouped by pixels with bare ground (top row), short stubble (second row), medium stubble (third row), and tall stubble (bottom row). Results of the pairwise K-S analysis (right column) are reported as the number of statistically significant tests ($p < 10^{-5}$) out of 100 total tests.

451 tests within medium stubble pixels, about 15% of the tests with bare ground
 452 pixels, and almost none of the tests within tall stubble pixels. Although we
 453 cannot state with confidence the reason for these differences, we do not be-
 454 lieve they are related to differences in fSCA or snow depth between mixed
 455 pixels of different stubble classes. For example, the mean fSCA for mixed
 456 pixels with bare ground, short stubble, and medium stubble are all between
 457 0.50–0.53 and the distributions are not significantly different from each other.
 458 Although more work is necessary to understand these fine details, these re-
 459 sults suggest that UAVSAR phase change may be able to separate snow-free
 460 and snowy pixels, but differentiating mixed pixels presents more of a chal-
 461 lenge. We also note the relative symmetry between the upper triangular
 462 and lower triangular entries in each of the four K–S result tables. Entries
 463 reflected across the diagonal represent essentially the same K–S comparison;
 464 the only difference is the relative order of the pixel groups passed to the K–S
 465 function in our analysis. We report the full table here for completeness, and
 466 to demonstrate that our repeat-testing method is insensitive to the ordering
 467 of compared distributions.

468 Figure 7 shows cumulative distributions of phase change for the four stub-
 469 ble classes grouped by the three snow cover classes. This is similar to the
 470 previous analysis in Figure 6 but allows us to examine differences in phase
 471 change related to vegetation independent of snow cover effects. As before,
 472 the diagonals of the K–S result tables in Figure 7 are all 0 and the upper and
 473 lower triangular entries exhibit relative symmetry. However, marked differ-
 474 ences are apparent in the K–S results compared to the previous analysis. A
 475 large majority of pairwise K–S tests did not indicate significantly different

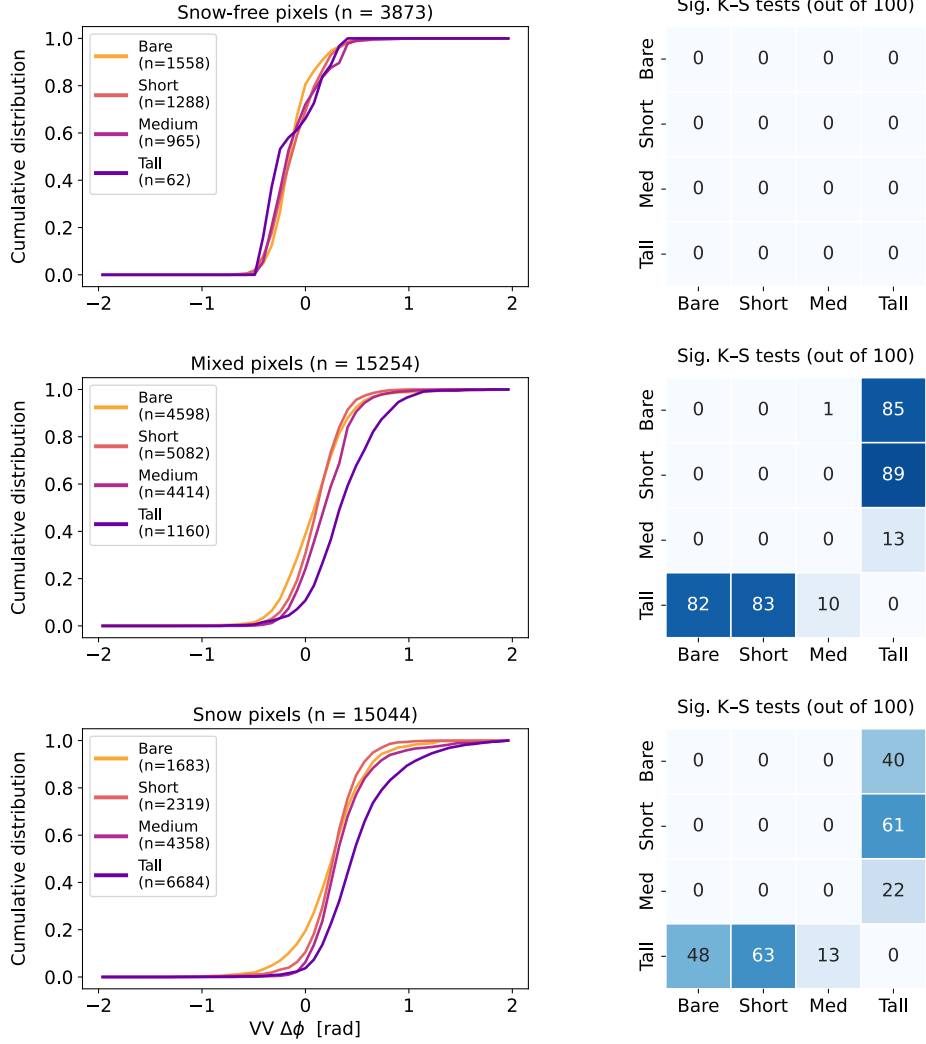


Figure 7: Cumulative distributions of VV phase change for the four stubble classes (left column), grouped by snow-free pixels (top row), mixed snow pixels (middle row), and snow pixels (bottom row). Results of the pairwise K-S analysis (right column) are reported as the number of statistically significant tests ($p < 10^{-5}$) out of 100 total tests.

distributions of VV phase change. For snow-free pixels (Figure 7, top row), phase change distributions between the four stubble classes were never found to be significantly different, indicating that UAVSAR VV measurements are not sensitive to the height of agricultural stubble in the particular layout at the study site. We note that these results may change for different crop types (i.e. crops with more shrub-like structure) or field layout (less regular crop rows). For mixed and snow pixels, no significant differences were indicated between phase change distributions over bare ground, short stubble, and medium stubble. However, phase change for tall stubble pixels was significantly different from the other three stubble classes within both mixed and snow pixels. The highest number of significant tests is between short stubble and tall stubble pixels that have mixed snow cover (more than 80% significant tests). Given the positive correlation between stubble height and snow depth shown in Figure 5b, we hypothesize that mixed snow, tall stubble pixels contain enough snow volume to affect the UAVSAR signal, even if the snow is irregularly distributed within a pixel. Mixed pixels in the other three stubble classes appear not to have sufficient snow volume to similarly affect the UAVSAR signal. The correlation between stubble height and snow depth also helps to explain the larger number of significant K-S tests between bare-tall and short-tall comparisons versus medium-tall comparisons. The non-significant findings for snow-free pixels (Figure 7, top row) provide additional evidence that these results are related to differences in snow, not differences in vegetation.

Taken together, we interpret the results shown in Figures 6 and 7 to indicate that UAVSAR VV phase change is modulated by differences in snow

501 cover but relatively unaffected by differences in agricultural stubble height.
 502 When controlling for stubble height, distributions of VV phase change are
 503 almost always significantly different between snow-free pixels and pixels with
 504 some amount of snow cover ('mixed' or 'snow' snow cover classes). These re-
 505 sults are encouraging and suggest that the InSAR-SWE method is not nec-
 506 essarily limited by the presence of exposed agricultural vegetation in prairie
 507 snowpacks. We note that these results are likely specific to the L-band data
 508 used in this experiment. A multi-frequency, tower-based setup like the one
 509 used by Ruiz et al. (2022) would be a great extension of our study. C- and
 510 X-band data were unable to penetrate the dense forest canopy in their study,
 511 but those frequencies may perform better over agricultural vegetation. How-
 512 ever, we expect that exposed stubble would have a greater decorrelating effect
 513 on higher-frequency measurements as compared to the L-band data used in
 514 this study. Leinss et al. (2015) noted that vegetation fixed by snow cover
 515 does not move and therefore does not contribute to decorrelation. Agricul-
 516 tural stubble only a few centimeters tall was fixed by snow in this study,
 517 but considerable portions of the tall stubble (> 27 cm) remained exposed
 518 above the top of the snowpack and susceptible to adjustment or movement
 519 by wind and blowing snow. Depending upon the stubble height and crop type
 520 (i.e. individual wheat stalks versus shrub-like vegetation), future studies in
 521 prairie environments may need to account for vegetation-related decorrela-
 522 tion effects. We also expect that our results would be different for shallow
 523 snowpacks with different vegetation, e.g. tundra environments or early-season
 524 snow in forested mountain regions.

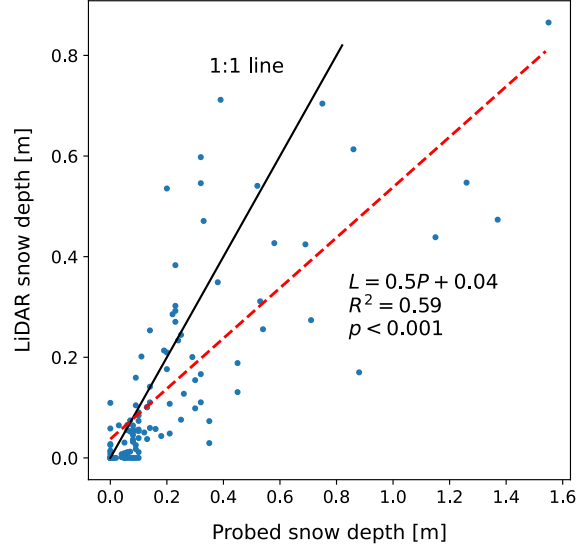


Figure 8: Comparison of probed and LiDAR-derived snow depth. The red dashed line shows the line of best fit derived using linear regression. The 1:1 line is shown in black.

5.2. InSAR SWE estimation and error analysis

Figure 8 shows a comparison of probed and LiDAR-derived snow depth. The best-fit line between the two datasets has a slope of 0.5 and an R^2 value of 0.59; overall, LiDAR snow depths are lower than the probed measurements and there is considerable spread in the differences, especially in deeper snow. Root-mean-square deviation between the two measurements is 0.20 m and the mean probe measurement is 0.22 m. RMSD in our study is on the order of the 0.09 m and 0.17 m reported by Harder et al. (2020) for LiDAR snow depth measurements in open and shrub-covered prairie environments, respectively. However, the relative magnitudes of RMSD and mean probed snow depth in our study indicate that LiDAR SWE estimates derived using

these snow depth measurements are not suitable to validate InSAR-derived SWE estimates on an absolute level. The best-fit line demonstrates that the LiDAR snow depths are positively correlated with in situ probed measurements, and a visual comparison between the LiDAR snow depths and UAV orthophoto indicates that the LiDAR is able to capture broad trends of snow accumulation. Although we cannot use the LiDAR data to quantify the absolute error associated with InSAR-based SWE estimates, we can individually normalize LiDAR- and InSAR-based SWE estimates and compare the two estimates on a relative basis. We apply min-max normalization to the snow depth datasets individually:

$$X' = \frac{X - X_{\min}}{X_{\max} - X_{\min}} \quad (8)$$

where X' the normalized pixel value, X is the original pixel value, and $X_{\min}$ and $X_{\max}$ are the global minimum and maximum of the dataset. This transforms the original SWE datasets to have a range of 0–1.

Figures 9a and 9b show normalized, spatially distributed LiDAR-derived and InSAR-derived SWE estimates. Gray areas in the panels mask out pixels with coherence less than 0.5 or fSCA less than 10%, for which SWE was not estimated. Prior to normalization, the LiDAR-derived SWE estimates ranged from –13 to 228 mm, while the InSAR-derived estimates ranged from –27 to 44 mm. The negative SWE estimates are an indication of the error present in the two datasets. Even with these different original ranges, individually normalizing the two estimates allows us to investigate if the two methods are capturing similar spatial patterns of SWE across the scene. To be explicit: the normalized range of 0–1 in the LiDAR- and InSAR-derived results (Figure 9a and 9b, respectively) represents different ranges in the

560 original, non-transformed datasets.

561 Some similarities between the two SWE estimates are visually appar-
 562 ent, especially in areas that feature stark transitions in the landscape. Both
 563 datasets show north–south running regions of relatively high SWE on the
 564 western edges of several fields. These correspond to locations across the
 565 field site with an increase in stubble height moving along the prevailing wind
 566 direction of west to east (Figure 1). The pronounced edge effects between
 567 shorter to taller stubble causes a sudden change in surface roughness, result-
 568 ing in preferential snow accumulation in these locations (Pomeroy and Gray,
 569 1995). The increased snow deposits are fairly confined to the western edges
 570 of the fields, and do not extend eastward to uniformly cover the entire field.
 571 This is perhaps a result of the small amount of snow available for transport
 572 associated with the individual storm event.

573 Substantial differences also exist between the two SWE estimations. As
 574 noted above, the range of the LiDAR-derived estimates is larger than that
 575 of the InSAR-derived estimates. This is visually apparent in the sharp con-
 576 trast between dark blue areas of high SWE on field edges and much lighter
 577 colors in the surrounding fields (Figure 9a). In comparison, the difference
 578 between these areas in the InSAR-derived estimates is less pronounced (Fig-
 579 ure 9b). Figure 9c shows the difference between the normalized LiDAR- and
 580 InSAR-based estimates. Although this quantity does not provide a meaning-
 581 ful comparison of the absolute SWE differences, considering the differences
 582 between these normalized datasets across the scene may still provide some
 583 insight. For example, if the difference were relatively constant scene-wide,
 584 it may be possible to simply multiply the InSAR-derived SWE estimates

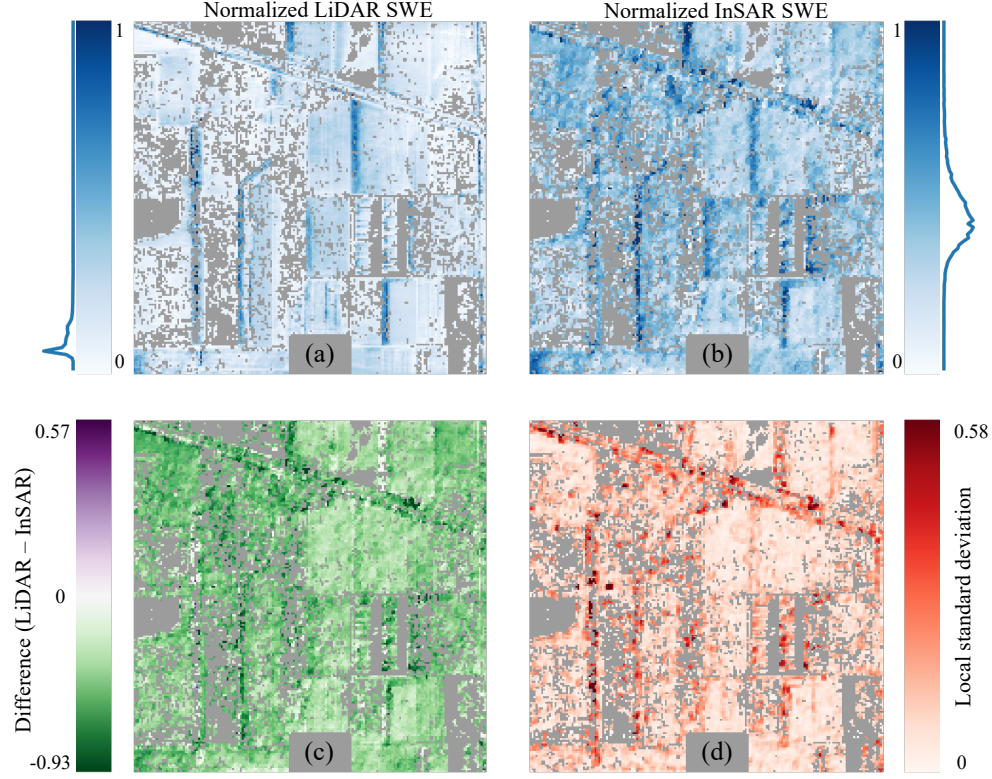


Figure 9: (a) Normalized LiDAR-derived SWE estimates. The original range was -13 to 228 mm. Distribution of measurements is shown to the left of the colorbar. (b) Normalized InSAR-derived SWE estimates. The original range was -27 to 44 mm. Distribution of measurements is shown to the right of the colorbar. (c) The difference between normalized LiDAR- and InSAR-derived measurements (Panel a minus Panel b). (d) Standard deviation calculated at each pixel using the central pixel and the 8 nearest neighbor pixels. Gray areas in all panels mask out pixels with coherence less than 0.5 or fSCA less than 0.1, for which SWE was not estimated.

by some constant to improve accuracy. Here the differences reflect a more complicated scenario. In almost all valid pixels over the study site, the difference between normalized LiDAR and normalized InSAR SWE estimates is negative, but those differences are not constant in space. A broad trend is apparent where areas of greater difference (darker green) are present in the western half of the scene, with areas of lesser difference in the eastern half. Differences within some fields are relatively uniform while other fields show strong local variation. Figure 9d shows the standard deviation at each pixel calculated using the 8 nearest neighbor pixels around the central point, a measure of local variability. Local variability is high in locations with relatively large SWE accumulation, typically located in the berm or along the western edges of fields.

The local spatial variability (Figure 9d) gives some insight into the complexity of the relationship between LiDAR- and InSAR-derived SWE measurements in a particular area. In areas of relatively low variability, the spatial patterns in the two estimates are relatively consistent, and simple scaling techniques may present a means of reducing error in the InSAR-derived SWE measurements in those areas. On the other hand, areas of relatively high variability indicate that spatial patterns differ considerably between the two methods, and that error reduction may be more challenging in these locations. Therefore, inspecting the surface characteristics of pixels with high and low variability may provide additional perspective into the conditions under which the InSAR-SWE method is more or less viable. We use the Getis-Ord G_i^* statistic (Getis and Ord, 1992) to identify clusters of high and low variability throughout the scene at various levels of statistical

610 significance (Figure 10).

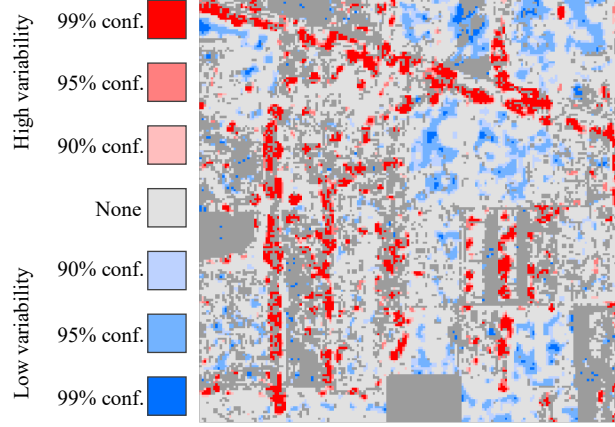


Figure 10: Results of Getis-Ord G_i^* analysis for local variability in the difference of the two SWE estimates (Figure 9d).

611 Figure 11 shows the distributions of stubble height, fSCA, and snow depth
 612 standard deviation separated into three groups based on the Getis-Ord G_i^*
 613 analysis: clusters of high and low variability with at least 99% confidence
 614 (i.e. $p < 0.01$; the darkest red and blue pixels in Figure 10), and pixels not
 615 identified statistically significant outliers (light gray pixels in Figure 10). A
 616 pairwise K–S analysis similar to the one described in Section 4.2 identified
 617 that for stubble height, fSCA, and snow depth standard deviation, the dis-
 618 tributions from high variability and low variability clusters were significantly
 619 different from each other in 100 out of 100 tests. For fSCA and stubble
 620 height, clusters of low variability were significantly different from non-outlier
 621 pixels in 90 out of 100 K–S tests. For snow depth standard deviation, clusters
 622 high variability were significantly different from non-outlier pixels in 90 out
 623 of 100 K–S tests.

624 With the results of the K–S analysis we can conclude that high variability

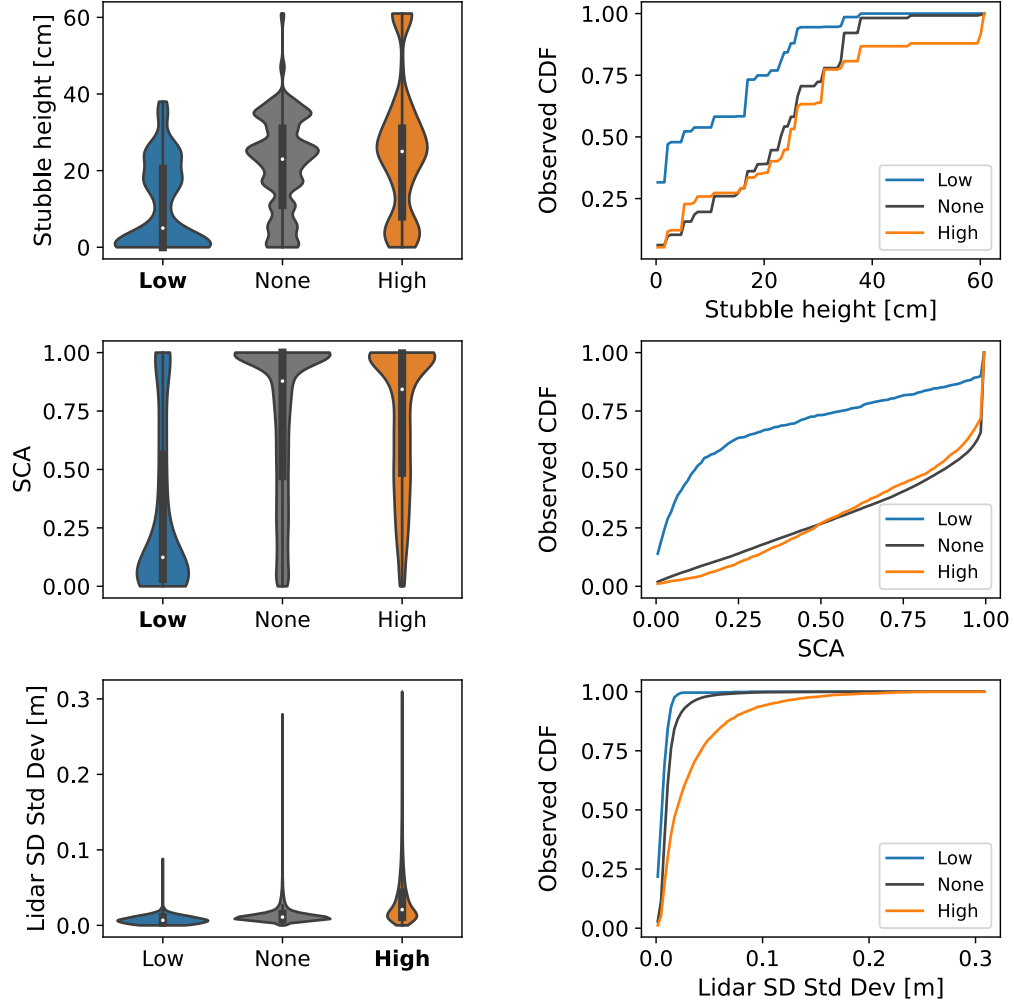


Figure 11: Distributions of stubble height (top row), fSCA (middle row), and LiDAR-derived snow depth variability (bottom row) separated by Getis-Ord G_i^* cluster results shown in Figure 10, and displayed with violin plots (left column) and observed CDF (right column). For all variables, distributions between clusters of high and low variability were found to be significantly different from each other using a K-S analysis. For a given variable, clusters of high or low variability that were found to be significantly different from non-outlier pixels are bolded on the x-axis.

pixel clusters have higher median fSCA, stubble height, and snow depth
 standard deviation as compared to low variability clusters. Because we use
 this local spatial variability as a comparison of the spatial patterns within
 LiDAR- and InSAR-based SWE measurements, we conclude that the two
 methods produce more similar results in pixels with lower fSCA, stubble
 height, and snow depth variability. These characteristics are closely related
 at our field site: pixels with short or no stubble entrain relatively less snow,
 and are therefore associated with less snow-covered area and lower snow
 depth variability. Pixels with taller stubble entrain more snow, leading to
 greater snow coverage in the pixel and deeper snowpacks (Figure 5). We
 also observe that the areas in the site with the deepest snowpack, the berm
 and the windward edge of some fields, correspond closely with clusters of
 high variability in Figure 10. We know from lidar snow depth measurements
 (Figure 1c), field photos (Figure 2), and time spent in the field during IOPs
 that snow depths in these areas exhibit high amounts of sub-grid spatial
 variability at the scale of this analysis. Snow depth variability is the only
 variable in Figure 11 for which the distributions between high variability
 clusters and non-outlier pixels were significantly different. Therefore, we have
 identified that sub-pixel snow depth variability, not stubble height or fSCA,
 is the primary characteristic that affects whether LiDAR- and InSAR-based
 SWE estimates will exhibit similar spatial patterns in a localized area.

5.2.1. *Error from snow-free pixels*

Snow-free pixels were masked out of the analysis and results described
 above using the UAV orthophoto. Figure 12 shows the distribution of VV
 phase change and associated erroneous Δ SWE estimations for snow-free pix-

els above the coherence threshold of 0.5 that would be calculated if these pixels had been left in the scene. Mean Δ SWE estimated for these pixels is -1.34 mm using (6). More concerning than the magnitude of these estimates is that they have the incorrect sign, and estimate a SWE loss after an accumulation event. This example illustrates the importance of masking out snow-free pixels, which could be irregularly distributed in prairie snow environments regardless of the time of year. Satellite-based InSAR data will typically not have matching optical imagery at equivalent spatiotemporal scales, which will make accurate, reliable pixel masking for this purpose more challenging. Although a harmonized SAR/optical product and workflow could provide better estimates of SWE in mid-latitude prairie environments, improvements for high-latitude tundra snowpacks would be minimal due to the lack of solar illumination for much of the winter.

5.3. *Limitations and suggestions for future work*

Field data collection for this study was made more challenging by windy conditions that grounded UAV operations. As mentioned in Section 3, UAV-derived datasets were collected one day after the second UAVSAR acquisition due to gusty conditions on 20 January. Despite the strong winds, we did not make a note of visibly blowing snow during field work on 20 January. Given the relatively small size of the snow event on 18 January, we expect that most wind redistribution of snow occurred between 18 and 20 January, and changes between 20 and 21 January were not large enough to significantly affect the results of this study. However, differences in the timing of data collection could play a larger role in future studies, especially if larger snow events are involved. Given the financial and logistical costs of airborne L-

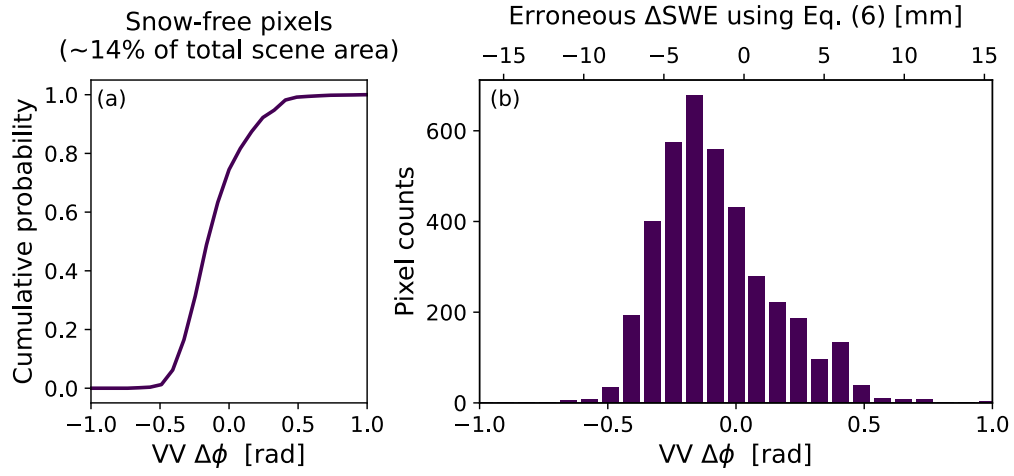


Figure 12: (a) Cumulative distribution of VV phase change over snow-free pixels, which were masked out of the primary analysis using the UAV orthophoto. (b) The same data presented as a frequency histogram of phase change on the bottom axis and the corresponding ΔSWE estimate using Equation (6).

band measurements and the high likelihood of weather-based interruption of
in situ data collection, future InSAR-SWE studies in prairie environments
may benefit from a ground-based (e.g. Ruiz et al., 2022) or space-based SAR
system. These would allow for more consistent measurements over a winter
season and would likely capture a wider range of snow-vegetation interac-
tions during early-, mid-, and late-season snowpacks. Soon the snow science
community will have access to regular L-band measurements on a 12-day re-
peat from the NISAR satellite mission, which will provide greater flexibility
to plan field work. We expect a combined L-band/C-band product created
from NISAR and Sentinel-1 data would reduce uncertainties in InSAR-based
SWE retrievals, and would provide additional insight into the effects of sub-
pixel snow depth variability and exposed vegetation effects. We also envision
opportunities to begin seasonal SWE measurements using L-band InSAR
techniques, then transition to higher-frequency backscatter techniques once
wet snow is detected later in the season.

The LiDAR-derived SWE estimations are based on LiDAR snow depth
measurements, which are generated by subtracting a snow-free DEM from
a snow-on DEM. LiDAR measurements generally underestimated true snow
depths (Figure 8), and the variation was large enough that we chose not use
LiDAR-based products as an absolute validation dataset. While overprobing
can introduce error into manual snow depth measurements, the ground at the
study site was very hard and we expect that very little overprobing occurred.
One possible source of LiDAR error is that our two DEMs were collected with
two different lasers: 1550 nm for the snow-free base model and 905 nm for
the snow-on model, which yields better pulse returns from snow and ice

700 compared to a 1550 nm laser (Rizza, 2021). The two wavelengths may have
 701 behaved differently over exposed stubble which may have led to differences
 702 in DEM generation from the original point clouds. We note that this issue
 703 would not necessarily be resolved by using a constant LiDAR wavelength,
 704 given the nature of snow-vegetation interactions in this environment. Future
 705 studies should also consider multiple permanent ground control points across
 706 the scene surveyed at very high accuracies, which would improve accuracy
 707 and decrease processing time of UAV LiDAR and photogrammetry datasets.

708 The uncertainty in our LiDAR snow depth data limited our analysis of
 709 the LiDAR- and InSAR-based SWE estimations to relative spatial patterns
 710 instead of absolute differences. Because of this limitation, we cannot state
 711 with certainty which method produces more accurate results. However, we
 712 expect that the LiDAR-based estimates would be more accurate overall, and
 713 especially over pixels with greater snow depth variability (the high variability
 714 clusters in Figure 10). Areas with relatively deep snowpacks have relatively
 715 shorter stubble extending above the top of the snowpack, which leads to greater
 716 certainty that the LiDAR returns are from the snow surface. The 30 cm
 717 LiDAR data is also able to capture much more of the spatial variability
 718 that exists in the SAR pixel. Also, Equation (6) assumes that the snowpack
 719 encountered by the incident microwave radiation is dry and homogeneous.
 720 Although it has been demonstrated that the InSAR-SWE technique works
 721 in a vertically-layered snowpack (Leinss et al., 2015), adjustments to the
 722 equation to account for horizontal heterogeneity have not been proposed.
 723 This is an interesting direction for future work, but we suggest that it should
 724 be attempted in a snowpack with fewer confounding factors like snow-free

725 areas and effects from exposed vegetation.

726 We also note that accurate SWE and snow depth measurements in this
 727 shallow and spatially variable snowpack are challenging regardless of the
 728 measurement technique employed. In some areas of the berm feature, snow
 729 depths varied in quasi-stochastic patterns on the order of a meter over hori-
 730 zontal distances of 0.5–1 m. We did not have the resources available to col-
 731 lect in situ probe measurements that would truly capture the nature of this
 732 spatial variability. However, the berm was not representative of scene-wide
 733 snowpack. UAVSAR pixels in other fields included areas of dense, 0.1–0.2 m
 734 deep snowpacks that transitioned to snow-free ground over very short dis-
 735 tances. Many probed snow depth measurements were less than 0.1 m, points
 736 which contained only a few millimeters of SWE. Although the LiDAR- and
 737 InSAR-based estimates differed by tens to hundreds of percentage points
 738 in some of these pixels, this still corresponds to absolute errors on the or-
 739 der of millimeters, which may be acceptable for some applications. Spa-
 740 tial variability over short distances is characteristic of prairie snowpacks in
 741 general (Sturm and Liston, 2021), but we expect that a deeper mid-winter
 742 snowpack would smooth out some of the variability we observed during this
 743 study. Hence our results do not indicate that L-band InSAR-SWE estimates
 744 are wholly inappropriate for prairie snowpacks, but instead establish some
 745 snowpack characteristics that represent “worst-case” conditions where the
 746 technique breaks down and produces unreliable estimates. Future studies
 747 should consider targeted observations that include many systematic probe
 748 measurements within individual SAR pixels (e.g. Lutz and Birkeland, 2011).
 749 Although time consuming, this technique may provide additional insight into

the effects of snow depth spatial variability on InSAR phase change. Future work investigating shallow snowpacks with less spatial variability may be able to quantify a minimum snow depth that L-band InSAR techniques can reliably measure. Again we suggest that this work should target snowpacks with fewer confounding factors than were present at our study site.

We illustrated the importance of masking snow-free pixels for InSAR-derived SWE estimates in prairie environments. Although a SAR/optical harmonized satellite product may be able to provide a mask in the absence of UAV optical data, such a product would not be feasible in high-latitude regions for most of the winter season. A snow-free mask would also be important for InSAR-SWE application over Arctic tundra snow, where vegetation effects on VV phase change may be erroneously interpreted as snow effects. Future work might include an investigation into a SAR-based snow cover mask, which has been tested in deep mountain snowpacks (Varade et al., 2020) but not prairie or tundra environments.

We also recommend a systematic investigation of L-band InSAR coherence over different snowpack regimes and vegetation types for future calculations of SAR-derived SWE. This approach will greatly benefit the effort towards understanding where regional-scale SWE measurements may be possible using L-band satellite measurements.

6. Conclusion

In this study we investigated the feasibility of using L-band InSAR data to estimate snow in an agricultural prairie environment. We focused on one InSAR pair collected by the UAVSAR airborne platform in the context

774 of variable snow depth, snow covered area, and agricultural stubble heights.
 775 Pairwise comparisons using the Kolmogorov–Smirnov (K–S) test showed that
 776 UAVSAR VV phase change is sensitive to differences in snow cover but rel-
 777 atively unaffected by differences in agricultural stubble height. However, we
 778 did not find similarly definitive results when we used the same phase change
 779 data to estimate SWE. Although broad spatial patterns were similar in nor-
 780 malized LiDAR-derived and InSAR-derived SWE estimates, the Getis-Ord
 781 G_i^* statistic identified statistically significant clusters where the two estimates
 782 exhibited high variability within small areas. By inspecting the pixels within
 783 these clusters, we identified sub-pixel snow depth variability as the charac-
 784 teristic most associated with differences between LiDAR- and InSAR-derived
 785 SWE estimates.

786 We view these results as promising for the future of InSAR-based snow
 787 measurement in prairie environments. In this shallow and heterogeneous
 788 snowpack, where accurate snow measurements are challenging regardless of
 789 the measurement technique, InSAR- and LiDAR-based SWE estimates dis-
 790 played similar spatial patterns. Our results suggest that absolute estimates
 791 will improve over snowpacks with less sub-pixel variability. Regular L-band
 792 measurements from the upcoming NISAR satellite present an opportunity to
 793 examine InSAR-SWE retrievals over a range of snow conditions in prairie en-
 794 vironments. Future work in the prairie may help quantify a minimum snow
 795 depth/SWE that can be reliably measured using L-band techniques. Our
 796 methodology provides a framework to combine remotely-sensed data from
 797 several platforms and examine the performance of InSAR-derived estimates
 798 in relation to various surface characteristics. While we have demonstrated

799 this technique for SWE estimates in a prairie environment, it could also be
 800 adopted in other snowpack regimes, or for InSAR-based measurements of
 801 other Earth system observation targets.

802 **Credit authorship contribution statement**

803 **Ross T. Palomaki:** Funding acquisition, Methodology, Formal analysis,
 804 Visualization, Software, Field data collection and curation, Writing – Orig-
 805 inal draft. **Eric A. Sproles:** Funding acquisition, Project administration,
 806 Supervision, Resources, Field data collection, Writing – Review & Editing.

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 816 Finally, we are grateful to two anonymous referees whose comments helped
 817 improve the manuscript.

818 **Appendix A. Instrumentation layout and meteorological timeseries**
 819 **data**

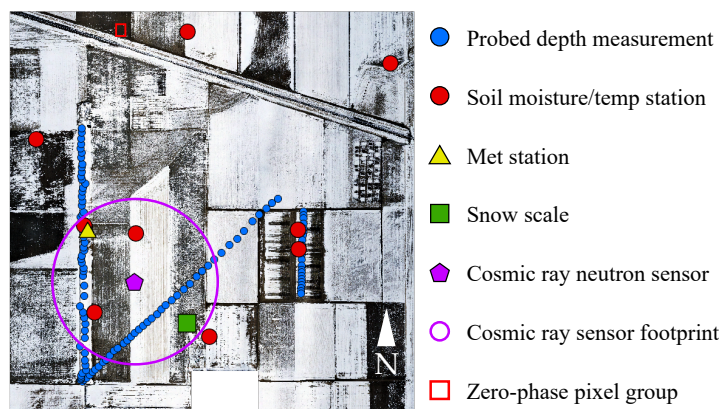


Figure A.13: Tower and measurement locations at the field site. The location of the 4×3 pixel group used to calculate the zero-phase point is marked near the top of the map with the red box. Soil temperature data from the nearby station marked with the black $+$ is shown in Figure A.14.

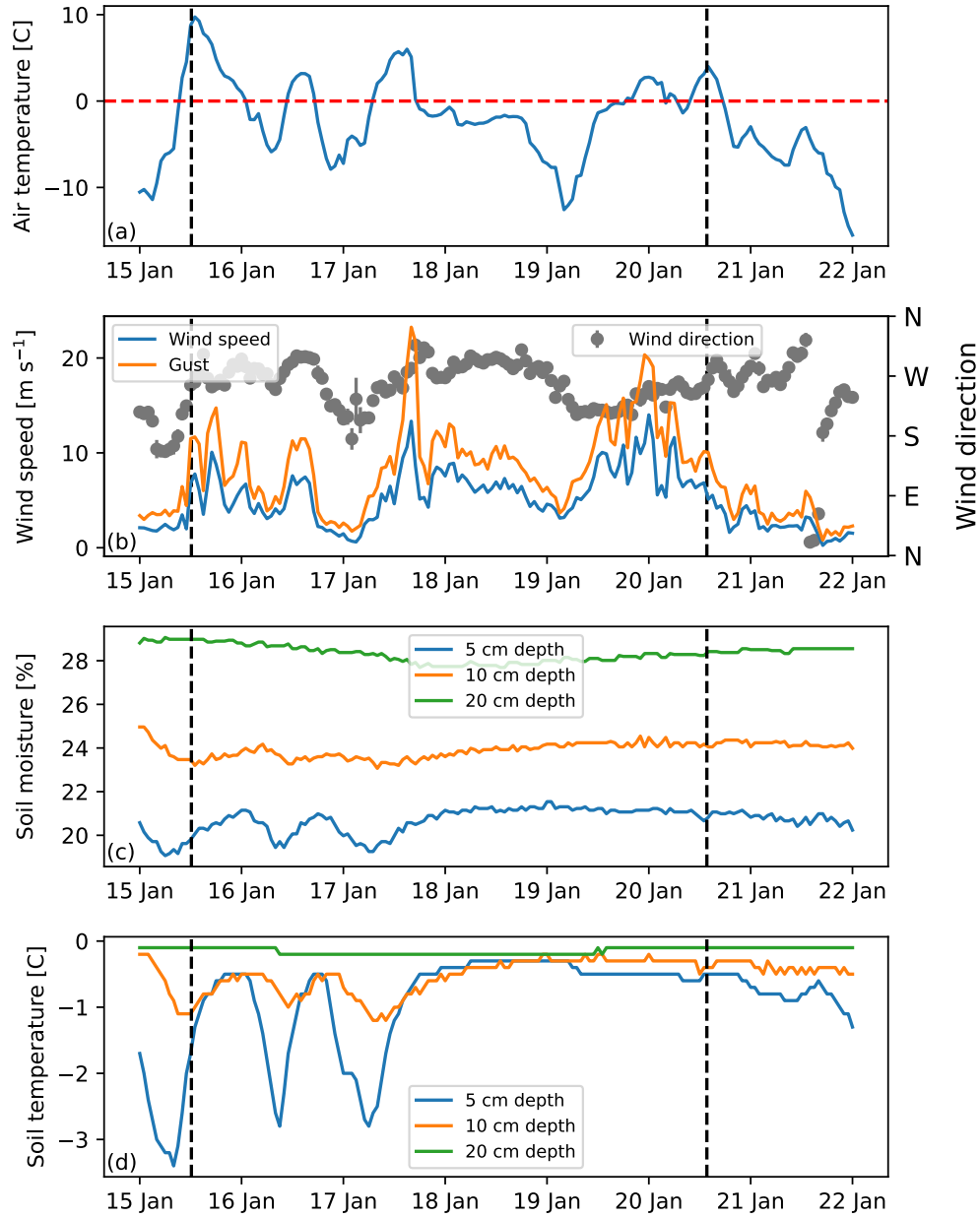


Figure A.14: (a) Air temperature and (b) wind speed and direction from the central weather station during the intensive observation period. (c) Soil moisture and (d) soil temperature data from the station marked with the black + in Figure A.13, the closest soil temperature measurements to the group of pixels used to calculate the zero-phase point.

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CONCLUSIONS AND FUTURE OUTLOOK

The work presented in this dissertation illustrates the importance of collecting high-resolution, spatially-distributed field measurements to validate SAR measurements of the cryosphere. The main conclusions presented here are all based on measurements of snow, ice, and surface conditions at the sub-pixel level with respect to SAR measurements. These measurements would not be feasible without the use of UAV technology. The river ice work presented in Chapters 2 and 3 has implications for improved operational river ice jam forecasting, while the research in Chapter 4 advances our scientific understanding of an important snow measurement technique in the Northern Great Plains.

In previous river ice studies, visually-apparent changes in surface roughness at the air-ice interface were frequently used to create validation datasets for ice cover maps generated from C-band satellite measurements. Surface roughness has the potential to influence SAR backscatter and is easily observed (not measured) on a spatially-distributed basis using aerial photography. While modeling and laboratory studies had demonstrated that other physical properties of river ice (bottom surface roughness, internal structural properties) could also affect SAR backscatter, these were typically ignored in previous field-based studies due to the difficulty of measuring these variables. In Chapter 2 of this dissertation I showed using high-resolution UAV-based measurements that river ice surface roughness, quantified using the standard deviation of surface height, is not a strong control on Sentinel-1 C-band SAR backscatter. Chapter 3 extended this work with a novel field-based river ice dataset that combined UAV, GPR, and traditional measurement techniques to show that Sentinel-1 backscatter contains information related to ice thickness and structure. Although the results from this chapter are site-specific and not broadly generalizable, they provide initial results that can guide future studies. Ice strength and the potential for ice jamming are more strongly tied to ice thickness and structure than to surface roughness; the fact that

Sentinel-1 measurements contain information about these jamming-relevant properties can be used for better interpretation of existing SAR-based operational river ice products.

The research in Chapter 4 is the first study to systematically investigate the feasibility of using L-band InSAR to measure snow presence and SWE in a prairie environment. High-resolution UAV-based snow presence, snow depth, and vegetation datasets enabled an in-depth analysis of the performance of existing InSAR algorithms, which had been developed primarily in alpine snow regimes. I used this dataset to show that L-band UAVSAR VV phase change is sensitive to differences in snow cover but relatively unaffected by differences in agricultural stubble height. However, even though InSAR- and LiDAR-based SWE measurements showed similar spatial patterns across the study site, absolute SWE measurements differed considerably between the two methods. I used robust spatial and traditional statistical methods to identify sub-pixel snow depth variability as the characteristic most associated with differences between LiDAR- and InSAR-derived SWE estimates. While it appears that L-band InSAR-SWE measurements do not perform well with large sub-pixel snow variability, the LiDAR data also showed considerable uncertainty in these areas when compared to probed snow depth measurements. It is important to recognize that the spatial variability of snow in prairie environments is difficult to measure regardless of the platform or technique.

The work in this dissertation provides guidance for future field campaigns. For river ice, UAV-GPR would provide better spatial coverage to match UAV-SfM surface roughness measurements. Ground-based or UAV-based C-band radar could better clarify scattering mechanisms relevant for Sentinel-1 measurements, due to the large difference in wavelength between Sentinel-1 and typical GPR frequencies. I expect that such datasets with improved spatial coverage would help generalize the results from small study areas up to rivers on regional or global scales. Repeat sampling at the same river location throughout the winter season would also help to generalize the results, and would provide additional insight

into river ice-SAR interactions during initial ice formation, mid-winter conditions, and the transition into the spring breakup season. Additionally, ice core samples would improve validation by providing more detailed information about the structural properties of the ice. Although ice cores require additional equipment and expertise compared to simpler ice thickness measurements, they would help separate the effects of small air bubbles or sediment in the ice versus larger air pockets between ice chunks in consolidated ice covers. Finally, there is ample room to explore different formulations of river ice surface roughness. The roughness metrics used in Chapters 2 and 3 are all based on the standard deviation of surface height. Metrics based on the length scale of variation (e.g. autocorrelation functions or semivariogram-derived metrics) might summarize river ice roughness in way that is more analogous to visually-determined roughness classes.

For field-based snow studies in prairie environments, strong winds and gusty conditions should be assumed and incorporated into all field work planning. For the study in Chapter 4, these conditions caused a one-day delay between the second UAVSAR acquisition and the UAV-based LiDAR and photogrammetry measurements. This delay had minimal effect on our results based on the small magnitude of the snow event that occurred over our study site, but differences in the timing of data collection could play a larger role in future studies, especially if larger snow events are involved. A tower-based setup (e.g. Ruiz et al., 2022) would be a great follow-up and expansion of the work presented in Chapter 4. Although upfront installation costs are high, tower-based SAR could provide denser temporal coverage over a winter season, and therefore more flexibility to conduct field work in favorable conditions. Tower-based SAR systems can also include multiple frequencies, which could make for more robust analysis of snow-microwave interactions in prairie environments with varying snow conditions over different months and seasons. This type of setup could enable a targeted investigation into the minimum snow depth that is reliably detected by L-band radar, which is an important threshold that will inform error analysis of future NISAR-

derived snow products.

Upcoming L-band SAR satellite missions will provide excellent opportunities to extend the work presented in this dissertation. Although not as regular as potential tower-based measurements, NISAR's 12-day repeat orbit will provide additional flexibility for field work timing for both river ice and prairie snow experiments, and the CARC field site will have a 3-day repeat due to its location within ascending and descending acquisitions. While the prospect of L-band river ice measurements is exciting on its own, there will be even more opportunity to combine NISAR data with other higher frequency SAR measurements, including C-band from Sentinel-1 or X-band from TerraSAR-X. A combined NISAR/Sentinel-1 product also has great potential for SWE measurements in all snow regimes, not just prairie environments. Additional data fusion products that incorporate L-band SAR with optical or hyperspectral satellite products have the potential to improve our capabilities to measure and monitor river ice, snow, and other components of the cryosphere at global scales.

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