

Application of GNSS Reflectometry for the Monitoring of Lake Ice Cover

by

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Author's Declaration

I hereby declare that I am the sole author of this thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners. I understand that my thesis may be made electronically available to the public.

Abstract

Lakes cover vast expanses of land in many regions of the Northern Hemisphere. Their presence has been shown to have a significant impact on local weather and climate. The seasonal presence of ice cover affects the transfer of energy and heat between lakes and the overlaying atmosphere, as well as various socio-economic activities, including transportation, recreation, and cultural practices. However, climate change is rapidly altering lake ice cover and its phenology and ice thickness with meaningful implications for both human activities and the ecosystems they support. Monitoring the seasonal variability and changes in lake ice cover and thickness is crucial for understanding the impacts of climate change; however, traditional in-situ observations have declined over the last few decades, creating a need for innovative remote sensing approaches.

Global Navigation Satellite System Reflectometry (GNSS-R) offers a novel, cost-effective method for monitoring lake ice dynamics. Unlike traditional remote sensing techniques, GNSS-R utilizes existing satellite signals (known as signals of opportunity), providing high temporal and spatial resolution data that can be used to detect and analyze lake ice conditions. This thesis investigates the application of GNSS-R for lake ice remote sensing, focusing on the signals' sensitivity to different phases of lake ice and its potential ice detection and the monitoring of lake ice phenology.

The thesis begins with an exploration of the fundamentals of GNSS-R and its relevance to lake ice remote sensing. Through understanding the scattering mechanisms involved when GNSS signals interact with lake ice, this research establishes a theoretical framework that supports the subsequent experimental analyses. The research then evaluates the sensitivity of GNSS-R signals, particularly the Signal-to-Noise Ratio (SNR), to various lake ice conditions. Using data from the Cyclone Global Navigation Satellite System (CYGNSS) mission over Qinghai Lake, the thesis

examines how SNR values change in response to freeze-up, ice cover, spring melt onset, and breakup. The results demonstrate that GNSS-R can effectively monitor lake ice dynamics with high temporal resolution, making it a valuable tool for tracking the seasonal evolution, inter-annual variability and changes in ice cover.

Further investigation is conducted on the potential of hybrid compact polarimetry in GNSS-R for analyzing lake ice cover properties. Data from the Soil Moisture Active Passive Reflectometry (SMAP-R) mission acquired over large Canadian lakes are analyzed to assess the sensitivity of polarimetric GNSS-R signals to ice cover conditions. The study finds that hybrid compact polarimetry enhances the interpretation of GNSS-R data, particularly in distinguishing between different ice and water conditions. In addition, the use of machine learning, specifically random forest, combining several polarimetric parameters, improves the accuracy of lake ice phenology detection compared to using each parameter alone. To deepen our understanding of how lake ice modifies the reflectivity of GNSS signals, a multi-layer scattering regime model is developed and validated against CYGNSS data. The model simulates the interaction of GNSS signals with various lake ice layers and the underlying water interface, providing insights into the complex scattering processes that influence GNSS-R measurements. The successful validation of the model demonstrates its utility for improving the accuracy of lake ice phenology analysis and offers a robust tool for broader cryospheric applications.

This thesis contributes to the field of remote sensing by demonstrating the effectiveness of GNSS-R in monitoring lake ice and advancing the understanding of GNSS signal interactions with ice-covered surfaces. The findings highlight the potential of GNSS-R as a low-cost, high-resolution tool for tracking lake ice dynamics, with implications for climate monitoring, weather forecasting and environmental management.

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Chapter 1 – Introduction

1.1. Motivation

Lakes are a prevalent physical feature in many regions of the Northern Hemisphere, particularly at high latitudes where they can cover 15% and 40% of the landscape (Duguay et al., 2003). Lakes and the presence/absence of ice cover play a critical role in controlling temperature and precipitation near their vicinity. The presence of lakes, as shown for the Mackenzie River Basin, increases the rate and duration of evaporation throughout the year (Rouse et al., 2005). Additionally, the presence and thickness of lake ice impacts the local economy, recreation, and culture. For example, relying on lake and river ice for transportation between northern communities (Knoll et al., 2019), over 3,800 tons of material were transported daily on the Tibbitt to Contwoyto winter road in 2020, including supplies from three diamond mines situated north of Yellowknife, Northwest Territories, Canada (Smith and Johnson, 2023). Lake ice also contributed to establishing recreational snowmobile trails, which drew over 75,000 tourists to the Haliburton Highlands/Ottawa Valley Region in 2018 (Ministry of Tourism, Recreation, and Sport of Ontario, 2021).

Climate change is altering the phenology and thickness of lake ice and threatening economic and recreational activities. Long-term trends in freeze-up and breakup from many lakes in North America, Sweden, Finland, and Russia indicate a reduction in freezing periods of an average of three days every decade (Hewitt, 2019; Lopez et al., 2019). Using climate model data (Dibike et al., 2011), it is expected that ice cover duration will be up to 50 days shorter for the period 2040–2079 compared to the 1960–1990 average. Therefore, due to the sensitivity of lake ice cover and lake ice thickness to changes in climate, it is critical to monitor, predict and understand its variations. In this regard, the World Meteorological Organization (WMO)'s Global

Climate Observation System (GCOS) identifies lake ice cover and ice thickness as two thematic variables of “Lakes” as an Essential Climate Variable (ECV), requiring daily lake ice cover monitoring with a maximum uncertainty of 10% and spatial resolution of 300 m, as well as monthly lake ice thickness measurement with a maximum uncertainty of 1–2 cm and spatial resolution of 100 m. These characteristics are chosen to collect sufficient data to comprehend lake variability in a changing climate (GCOS 2022a). That said, due to the large number and density of lakes across the Northern Hemisphere, manual measurements are difficult to obtain. For instance, the "Global Lake and River Ice Phenology" database (Benson et al., 2013) had up to 1046 observations in 1980 and only 165, on average, per year between 2010 and 2020.

To counterbalance the reduction of in-situ lake ice monitoring, remote sensing has become increasingly popular (Duguay et al., 2015). Remote sensing observations provide regular monitoring at spatial resolutions ranging from medium (ca. 250–1000 m) to high (ca. 10–100 m) in areas with dense lake coverage. By employing this approach to monitor lake ice cover and thickness, one may contribute to the expansion of existing ice records. Nonetheless, although, for example, microwave sensors function in all weather and daylight circumstances, their instrumentation is typically expensive for higher temporal and spatial resolutions due to intricate board designs and high-power requirements. Meanwhile, Global Navigation Satellite System Reflectometry (GNSS-R) offers a breakthrough remote sensing technology that is low-cost and has a high temporal and spatial resolution, making it useful for a range of ocean and land applications (Zavorotny et al., 2014).

In general, multipath GNSS signals have so far shown some potential for studying some aspects of cryosphere, including sea ice and soil freeze/thaw in permafrost regions. The potential of GNSS-R, however, has not yet been examined for studying the impact of lake ice on reflected

GNSS signals in order to detect lake ice and determine dates associated with its phenology. Conducting GNSS-R lake ice investigations over frozen lakes using different platforms sheds further light on lake ice studies, including lake ice detection and the determination of ice-on and ice-off timing.

1.2. Research Objectives

The primary objective of this thesis is to evaluate the sensitivity of GNSS-R signals in capturing different phases of lake conditions, including open water, ice cover, freeze-up, spring melt onset, and breakup. This is achieved by analyzing various parameters such as Signal-to-Noise Ratio (SNR), Normalized Bistatic Radar Cross Section (NBRCS), and polarimetric parameters. Through detailed experimentation and data analysis, the thesis aims to determine how GNSS-R can effectively detect and monitor these phases, thereby contributing to the understanding of lake ice dynamics and the development of a novel monitoring tool.

Another key objective is to assess the potential of GNSS-R for lake ice detection and phenology analysis using two distinct platforms: the Cyclone Global Navigation Satellite System (CYGNSS) and the Soil Moisture Active Passive Reflectometry (SMAP-R) mission. The thesis explores the application of these platforms in different environmental settings to evaluate their efficacy in monitoring lake ice. Additionally, the research involves modeling how lake ice modifies reflected GNSS signals by employing a multi-layer scattering regime model, which provides insights into the complexities of GNSS signal interaction with ice-covered surfaces.

1.3. Thesis Outline

This thesis is structured in a manuscript format and contains a total of six chapters. The first chapter introduces the motivations behind the research, focusing on the fundamental aspects of GNSS-R and its relevance to remote sensing of lake ice. It emphasizes the importance of monitoring lake ice using GNSS-R to understand its implications for climate studies and local economies. Chapter 2 delves deeper into the basics of GNSS-R, exploring its connection to lake ice, active microwave signals, and the broader application of GNSS-R in cryosphere remote sensing.

Chapter 3 evaluates the sensitivity of GNSS-R signals, specifically SNR values, to different phases of lake ice, including open water, freeze-up, ice cover, spring melt onset, and breakup. The chapter presents an analysis of GNSS-R data from the CYGNSS mission over Qinghai Lake, examining the impact of surface conditions on reflected GNSS signals and determining lake ice phenology with a high temporal resolution. This chapter is a peer-reviewed contribution published in *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*:

Ghiasi, Y., Duguay, C. R., Murfitt, J., Asgarimehr, M., & Wu, Y. (2023). Potential of GNSS-R for the monitoring of lake ice phenology. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*. <https://doi.org/10.1109/JSTARS.2023.3330745>

Chapter 4 investigates the potential of GNSS-R for detecting/monitoring lake ice phenology timing using hybrid compact polarimetry from SMAP-R data over four Canadian lakes. The chapter discusses the analysis of lake ice surface conditions, the accuracy of lake-wide ice fraction and ice phenology timing retrievals, and the implementation of regression analysis using Random Forest models. This chapter has been submitted to *Remote Sensing of Environment*:

Ghiasi, Y., Duguay, C.R., Rodriguez-Alvarez, N., Muñoz-Martin, J.F., & Bosch-Lluis, J. Analysis of full polarimetry GNSS-R sensitivity to lake ice cover properties. Submitted to *Remote Sensing of Environment*. Manuscript number RSE-D-24-03164.

Chapter 5 develops a multi-layer scattering regime model to simulate the sensitivity of GNSS-R reflectivity to lake surface conditions, specifically focusing on open water and lake ice scenarios. This model was developed based on CYGNSS observations over Qinghai Lake, and Spire grazing angle observations over Great Bear Lake and Great Slave Lake. The study provides insights into how these datasets can differentiate lake ice from open water based on reflectivity variations, contributing to advancements in lake ice monitoring through space-based GNSS-R data. This chapter is planned for submission to *IEEE Geoscience and Remote Sensing Letters*.

Chapter 6 summarizes the findings presented in the previous chapters, outlines the limitations of the research, and highlights areas for future research. Chapters containing published materials or currently under review are provided in their original format and are subject to copyright. The inclusion of these manuscripts in their original format results in some duplication of equations, sensor descriptions, and methodologies between chapters.

Chapter 2 – GNSS-R and Lake Ice Fundamentals

2.1. Global Navigation Satellite Systems

GNSS signals from the US Global Positioning System (GPS) satellites are the most widely used for both positioning and remote sensing and since they are central to the studies presented in this thesis, they are detailed here more thoroughly than other systems.

The first GPS satellite, OPS 5111 (NAVSTAR 1), was launched in 1978 as part of the Block I series, demonstrating positioning capabilities. Initially, the system was designed for 24 satellites, but it has grown to 31 operational satellites today. As the system evolved, satellites were built in different blocks and placed in various orbital planes. Table 2-1 provides the GPS constellation status as of September 10, 2019. GPS currently transmits signals using three L-band frequencies: the legacy L1 at 1575.42 MHz, L2 at 1227.60 MHz, and the more recent L5 at 1176.45 MHz, transmitted by satellites from Block IIF onward. GPS signals are generated through Direct Sequence Spread Spectrum (DSSS) modulation, which involves binary biphasic modulation. DSSS modulation combines three components: a Radio Frequency carrier, a navigation signal, and a spreading sequence, as depicted in Figure 2-1. GPS signals are circularly polarized with right-handed orientation (RHCP); on the other hand, reflected GPS signals mostly form the left-handed orientation (LHCP).

Table 2-1. GPS constellation status as of September 10, 2024.

Block	Launch Date	Carriers	Codes	No. of Sats
IIA	1990-1997	L1	C/A	0
IIR	1997-2004	L1 – L2	C/A – P	7
IIR-M	2005-2009	L1 – L2	C/A – P – L2C	7
IIF	2010-2016	L1 – L2 – L5	C/A – P – L2C – M – L5C	11
III/IIF	2018-present	L1 – L2 – L5	C/A – P – L2C – M – L5C – L1C	6
Total number of operational GPS satellites				31

The signal model for an unaltered direct signal transmitted by a GNSS satellite can be represented as a carrier wave with the amplitude of A and frequency of f modulated by the spreading sequence $c(t)$ and the navigational data $d(t)$. The navigation signal consists of amplitude-modulated rectangular pulses at 50 Hz, where binary values define the pulse polarity. The spreading sequence is a rectangular pulse based on a PseudoRandom Noise (PRN) code. As shown in Figure 2-1, during DSSS modulation, the navigation and spreading signals, represented by sequences of +1 and -1, are multiplied to create a biphasic modulation function to be then multiplied with the carrier, resulting in the final transmitted signal as follows:

$$T(t) = A d(t)c(t) e^{-j2\pi f t} \quad (2 - 1)$$

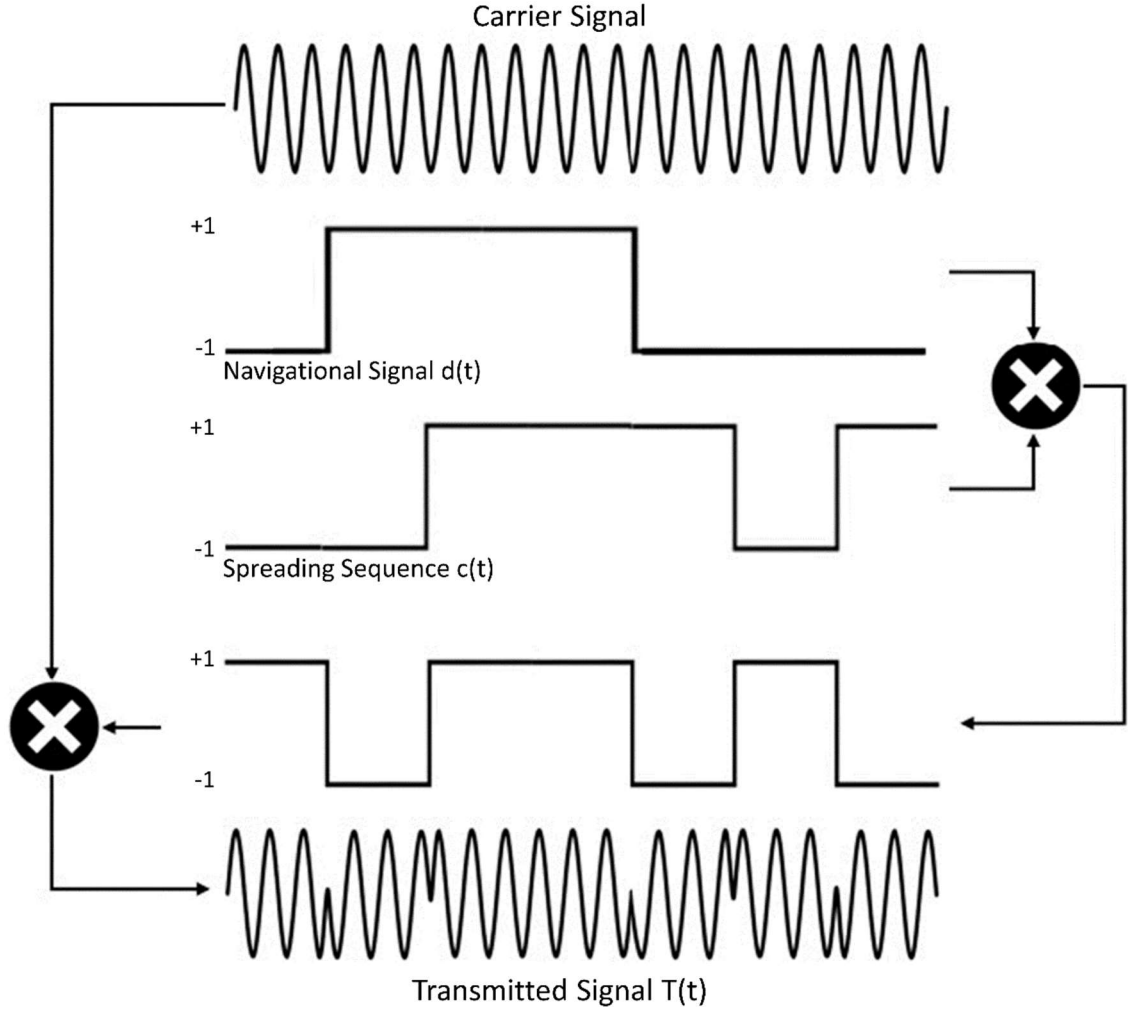


Figure 2-1. Transmitted GNSS signal structure based on the DSSS modulation.

After the signal propagates to the receiver, the GNSS component, $T(t)$, is altered resulting in the received signal $R(t)$. This signal retains an amplitude B after being affected by factors such as free-space path loss, antenna gains, atmospheric losses, and other linear scaling effects. The signal also undergoes a time delay τ and a Doppler shift D . Consequently, the GNSS signal component takes on the following general form upon reception by the receiver:

$$R(t) = B d(t - \tau) c(t - \tau) e^{-j2\pi(f+D)t} \quad (2 - 2)$$

PRN codes are deterministic and can be reproduced precisely. Each GPS satellite transmits a unique PRN code, allowing users' receivers to differentiate signals and identify transmitters, preventing interference between signals from different satellites. PRN codes exhibit Gaussian-like behavior when cross- or auto-correlated, designed to have significant autocorrelation and low cross-correlation peaks. Therefore, by conducting a cross-correlation between locally generated PRN codes with those being received from each satellite, the receiver is able to identify the transmitter GPS satellite, determine the delay based on the auto-correlation peak, and calculate the distance to the GPS satellite. Figure 2-2 shows examples of cross-correlation of a locally generated PRN code with two other received PRN codes (left) along with its autocorrelation with the same PRN code received from a GPS satellite (right). The significant autocorrelation peak helps the receiver to, firstly, detect the GPS satellite from which the signal is being received and, secondly, determine the delay parameter τ for this specific PRN code.

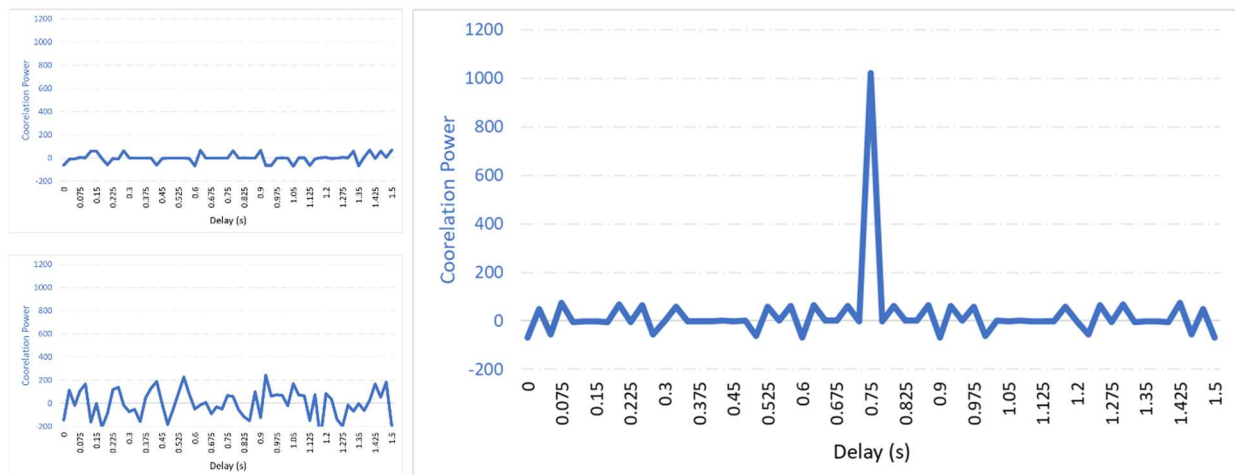


Figure 2-2. (Left) two examples of cross-correlation of a PRN code with two other received PRN codes, and (right), the autocorrelation with the same PRN code received from a GPS satellite. The autocorrelation peak denotes the delay parameter τ .

Blocks IIA and IIR broadcast only the original C/A code and restricted P-code, now known as legacy GPS signals. The C/A code on L1 is publicly available, while the P-code on both L1 and

L2 is reserved for military use and referred to as Y-code when encrypted. C/A PRN codes are derived from 1023-chip Gold codes (Gold 1967) at a frequency of 1.023 MHz, while Y-code PRN codes are generated at 10.23 MHz and reserved for authorized users. Block IIR-M and later satellites introduced new signals: L2C on L2 (the second civilian signal) and M-code on both L1 and L2. M-code is designed to be more resistant to jamming, with energy peaks located away from the existing P(Y) and C/A signals. L5, the third civilian signal, is broadcast in the 1176 MHz radio band, dedicated to aeronautical radionavigation services and providing increased robustness for critical applications. It was first broadcast by SVN 49 in Block IIR-M, and all Block IIF satellites now transmit it. Finally, L1C, the latest civilian signal on L1, is transmitted by Block III satellites, the first of which launched in late 2018 (Thoele et al. 2019).

GLONASS is the second system in operation on a worldwide scale that has been rejuvenated since October 2011 and now provides the service with 24 satellites. It sent navigation signals in three L-band sub-bands. While each GPS satellite has its own unique PRN, GLONASS satellites share one and use separate carrier frequencies. In other words, each satellite emits a unique carrier frequency, which enables receivers to identify the transmitter through frequency differentiation. Moreover, Galileo is the European navigation satellite system. Two demonstration satellites were launched in 2005 and 2008, and the constellation's first satellite was launched in 2011. While the constellation's completion has been sluggish, it has sped dramatically during the last two years. Three medium Earth orbital (MEO) planes are proposed for the satellites. The most recently launched four satellites E11, E13, E15, and E33 began active on February 11, 2019. Galileo works on three distinct frequency bands and transmits five distinct radio frequency signals: E1, E6, E5, E5a, and E5b with frequencies of 1575.42, 1278.75, 1191.795, 1176.45, and 1,207.14 MHz, respectively. BeiDou, also referred to as COMPASS, is China's worldwide navigation

system (Han et al. 2011). This constellation's first generation (BeiDou-1) was launched in 2000. It now consists of 40 satellites, of which 33 are operational (as of August 2019). On medium, geostationary, and inclined geosynchronous orbits. All satellites of the new generation emit their navigational signals at distinct frequencies: B1 (1,561.098 MHz), B2 (1,207.140 MHz), and B3 (1,207.140 MHz) (1,268.520 MHz). More details on GNSS can be found at Langley et al. (2017).

With regard to GPS, GLONASS, Galileo, and Compass compatibility and interoperability, transitioning from GPS-R to GNSS-R may be relatively easy, as reflectometry is less restricted than positioning interoperability.

2.2. GNSS-R: The concept

2.2.1. Introduction

The field of GNSS-R has seen significant advancements since its inception. The concept was first demonstrated through an airborne experiment in 1998 by Hall and Cordy (1998), and earlier in 1993 for sea altimetry by Martin-Neira (1993). Over the past two decades, the development of GNSS-R has been supported by increasing resources and the formation of specialized teams for recent satellite missions, resulting in rapid knowledge growth in the field. Contributions to this expansion have come from various sectors, including academia, research institutions, and industry, solidifying GNSS-R's place in the broader remote sensing community. The field has recently experienced a sharp rise in publications, now accounting for nearly 1% of all remote sensing research outputs (Rodriguez-Alvarez et al., 2023a).

GNSS-R operates as a bistatic radar technique utilizing signals of opportunity transmitted from GNSS satellites. These signals scatter off the Earth's surface and are received by a GNSS receiver, which can be positioned on various platforms, including ground-based instruments,

aircraft, or satellites. Each platform offers distinct advantages in terms of spatial and temporal resolution. Ground-based platforms offer high-resolution data but are limited in spatial coverage. Airborne platforms provide regional coverage with spatial resolutions between 300 m and 1 km, while satellite platforms can offer global coverage with spatial resolutions ranging from 1 km to hundreds of kilometers, depending on surface characteristics. The scattered GNSS signals are influenced by the roughness and dielectric properties of the Earth's surface, such as soil moisture, vegetation water content, and the presence of water bodies or frozen soil. Figure 2-2 depicts a scheme of different platforms of GNSS-R as a remote sensing tool.

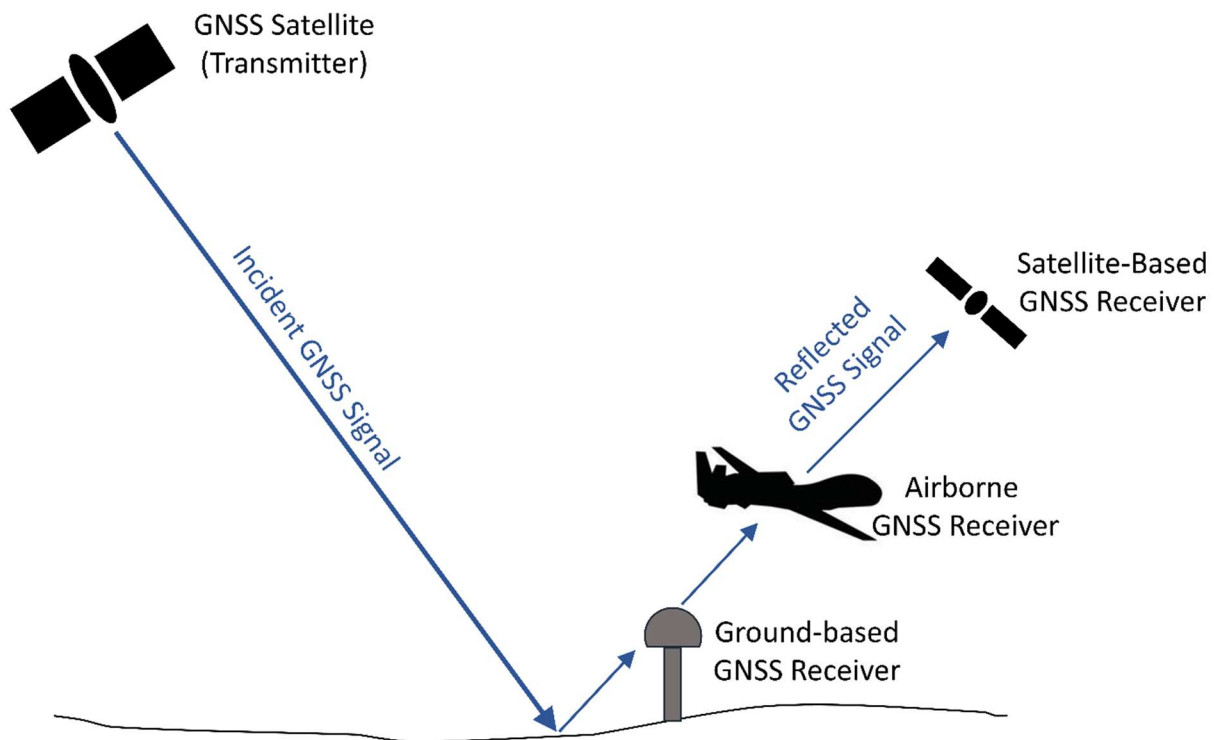


Figure 2-3. Scheme of GNSS-R for different receivers, i.e., ground-based, airborne, and satellite-based GNSS-R receivers.

Initially proposed for sea altimetry, the interferometric GNSS-R (iGNSS-R) technique was introduced by Martin-Neira (1993), utilizing the cross-correlation of direct and reflected signals,

particularly leveraging large-bandwidth military codes for high-precision altimetry. Following this, the more widely used conventional GNSS-R (cGNSS-R) technique was developed by Katzberg and Garrison (1996), employing a down-looking, left-hand circularly polarized (LHCP) antenna. Additionally, ground-based GNSS-R applications have been explored through GNSS interferometric reflectometry (GNSS-IR), a technique that uses a geodetic GNSS receiver to observe interference patterns created by the combination of direct and reflected signals, which are then used to infer various land surface properties (Zavorotny et al., 2009).

2.2.2. Theory

As with conventional measurements, which is the most common configuration of GNSS-R space missions, such as CYGNSS (Cyclone GNSS), a GNSS-R sensor correlates the reflected signal over a coherent integration time T_i (Voronovich and Zavorotny 2017a):

$$Y^c(T, \tau, D) = \frac{1}{T_i} \int_t^{t+T_c} s_R(t') a(t' - \tau) e^{-j2\pi(F_c+D)t'} dt' \quad (2-3)$$

where $s_R(t')$ is the PRN code sequence replica, $a(t)$ denotes the reflected signal, t denotes the integration start time, τ denotes the time delay, and D denotes the Doppler frequency shift. The reflected power is weaker than the direct one; thus, an incoherent average over a large number of observations, N_i , is used to get a better approximation (Voronovich and Zavorotny 2017a):

$$\langle |Y^c(\tau, D)|^2 \rangle \approx \frac{1}{N_i} \sum_{n=1}^{N_i} |Y^c(t_n, \tau, D)|^2 \quad (2-4)$$

When the Doppler frequency shift is zero, or $D = 0$, the observations represent a one-dimensional waveform. Adding other Doppler frequencies, the observations can be displayed as a two-dimensional map of the correlation power as a function of delay and Doppler shift, known as

delay-Doppler map (DDM). Two DDM examples are shown in Figure 2-4, which were recorded by CYGNSS over Qinghai Lake, Tibetan Plateau (China), during two different lake conditions, i.e. (left) during wintertime, where the lake surface was fully frozen and (right) during summertime, where the lake surface was ice-free (open water). Geophysical information may be derived from scattered signals only if one understands how the signals behave in response to the surface scattering properties. In GNSS-R research, as well as other radar studies, the reflective surface governs the scattering of signals through the Bistatic Radar Cross Section (BRCS) sigma nought (σ^0).

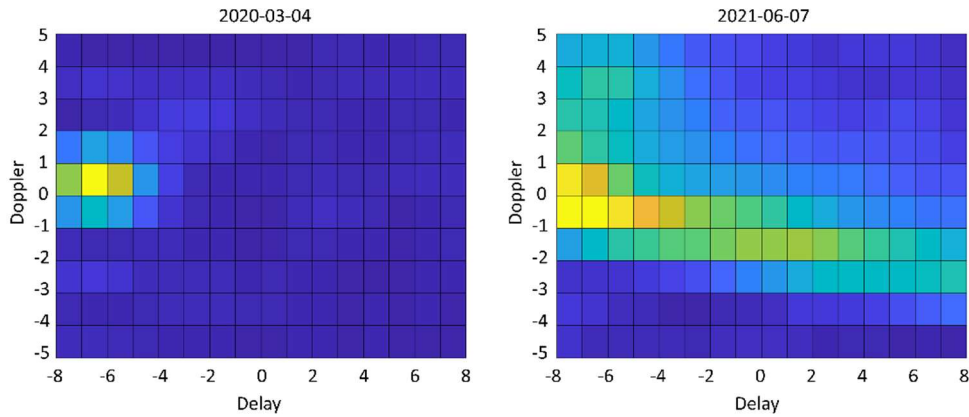


Figure 2-4. Two CYGNSS DDMs from Qinghai Lake, Tibetan Plateau (China), during (left) wintertime, when the lake is fully frozen, and (right) summertime, when the lake is ice-free.

Zavorotny and Voronovich (2000) developed the commonly used bistatic radar equation (BRE) for practical applications by using the Kirchhoff Approximation under the Geometric Optics limit (KA-GO). This approximation assumes that the electromagnetic (EM) field is created by reflections from a large number of specular spots inside the glistening zone. As a result, KA-GO is based on quasi-specular scattering and disregards diffraction effects. The ensemble mean of the correlation power as a function of time delay and Doppler frequency shift is as follows (Zavorotny and Voronovich, 2000):

$$\langle |Y(\tau, D)|^2 \rangle = \frac{P_t G_t \lambda^2 T_i^2}{4\pi^3} \iint \frac{G_r |\chi(\tau, D)|^2}{R_t^2 R_r^2} \sigma^0 dA \quad (2-5)$$

where $\chi(\tau, D)$ is the Woodward Ambiguity Function (WAF), which may be approximated by $\chi(\tau, D) \approx \Lambda(\tau)S(D)$, where Λ and S are the triangle and sinc functions, respectively, and τ and D , respectively, denote the time delay and frequency offset. $Y(\tau, D)$ denotes the ensemble mean of the correlation as a function of time delay and frequency offset, $P_t G_t$ forms the transmitter's Effective Isotropic Radiated Power (EIRP), and G_r denote the antenna gain of the receiver. The carrier wavelength is denoted by λ , the coherent integration time is denoted by T_i , the transmitter to specular point and specular point to receiver ranges are denoted by R_t and R_r , respectively, the glistening zone is denoted by A , and the BRCS (σ^0) is defined based on the KA-GO as a function of the polarization-dependent Fresnel reflection coefficient, which is controlled by the incident angle and the complex dielectric constant of the reflective layer (Zavorotny et al., 2014).

However, in the lake ice scenario, as GNSS signals are scattered by the ice, the Rayleigh parameter is not sufficiently large to account for substantial diffuse scattering. Rayleigh coefficient R_a is a physical measure used to classify different forms of electromagnetic wave scattering and is defined as follows (Voronovich and Zavorotny 2017b):

$$R_a = (2\pi/\lambda)h \cos \theta \quad (2-6)$$

where θ is the incidence angle, and h represents the root-mean-square of the surface heights as a function of the roughness spectrum of the surface. In this scenario, a coherent scattering component occurs that cannot be neglected, as implied by Equation 2-3. In this case, the KA-GO would result in an imprecise assessment of the BRCS via the probability density function (PDF) of surface slopes. Thus, one should employ models designed for more general scenarios to account

for the transition between weak and strong diffuse scattering, as well as their combination. More details on GNSS-R modeling for lake ice scenarios will be presented in Chapter 5.

2.2.3. Space-Borne GNSS-R Advancements

The first space-based GNSS-R signal was captured during a calibration routine of the Space Shuttle radar imager in 2002 (Lowe et al., 2002), which marked a significant milestone in the development of GNSS-R as a remote sensing tool. Following this achievement, in 2003, the UK Disaster Monitoring Constellation-1 (UK-DMC-1) mission from Surrey Satellite Technology Limited (SSTL) launched the first dedicated GNSS-R receiver into space. The UK-DMC-1 mission employed a four-element patch nadir-looking antenna array with left-hand circular polarization (LHCP). Its primary objective was to prove the concept of using GNSS-R for ocean studies by capturing small datasets that could be analyzed to understand the reflection of GNSS signals over the ocean surface (Unwin et al., 2013).

Building on the success of UK-DMC-1, the UK-TDS-1 mission was launched in 2013, featuring an upgraded version of the SSTL GNSS-R receiver known as SGR-ReSi. This receiver, which utilized the same antenna type as UK-DMC-1, operated using a correlator approach, called zoom transform correlator, a technique adopted by most GNSS-R receivers for processing reflected signals. The details of this approach are provided in Jales (2012). The UK-TDS-1 mission was designed with a polar orbit, which enabled it to collect data over oceans, land, and ice, thereby broadening the scope of GNSS-R applications beyond just ocean observation. The mission significantly contributed to the growing body of knowledge regarding the use of GNSS-R in different environments (Unwin et al., 2016).

In 2016, NASA launched the CYGNSS mission, a constellation of eight microsatellites designed to study tropical cyclones. The mission was built upon the correlation approach of SGR-ReSi, while using two sets of side-looking LHCP antenna arrays placed on the sides of each satellite to ensure larger coverage. Covering the mid-latitudes ($\pm 38^\circ$), CYGNSS provided a unique platform for GNSS-R research, particularly for ocean and land observations (Ruf et al., 2019).

Private companies have also made notable contributions to space-based GNSS-R. Spire Global Inc. launched a series of CubeSats in 2019 and 2020 with GNSS-R capabilities. These CubeSats feature miniaturized receivers capable of multi-constellation operations (GPS, Galileo) and 20 simultaneous correlation channels. The antenna system, which consists of a 3 LHCP patch array, enables Spire's CubeSats to operate continuously with deployable solar panels. Spire's constellation combines GNSS-R and GNSS radio occultation (GNSS-RO) measurements, capturing LHCP signals at near-nadir and RHCP signals at grazing angles, thus expanding the range of GNSS-R applications (Jales et al., 2020)

The upcoming HydroGNSS mission, scheduled for launch in 2025, is set to feature the latest version of SSTL's SGR-ReSi receiver, which is called the SGR-ReSi-Z. This receiver will provide multi-constellation (GPS/Galileo), multi-polarization (LHCP/RHCP), and multiband (L1/L5) GNSS-R measurements. A TechDemoSat mission, DoT-1, was launched in 2019 to evaluate the new satellite bus used for HydroGNSS. (Unwin et al., 2021). Additionally, the Soil Moisture Active Passive (SMAP) radar, although not specifically designed for GNSS-R, has contributed to the field through its collection of GPS L2C. Known as SMAP-reflectometry, these data offer valuable insights into polarimetric applications of GNSS-R over land, further broadening the scope of GNSS-R research and applications. More details on SMAP-R missions will be provided in Chapter 4 of this thesis.

2.2.4. GNSS-R in Cryosphere Remote Sensing

A substantial amount of spaceborne GNSS-R data has been gathered for cryosphere studies, including sea ice, ice sheets, and permafrost freeze/thaw analysis. The data comes from frequent measurements taken by TDS-1 and SMAP-R across the polar regions, as well as CYGNSS observations over the Tibetan Plateau.

Several studies have demonstrated the capabilities of GNSS-R for sea ice detection and classification using data from various satellite missions. Yan and Huang (2016) introduced a sea ice detection method using GNSS-R DDMs, observing less spreading along the delay and Doppler axes for sea ice compared to seawater. Their approach applied an adaptive incoherent summation to increase the signal-to-noise ratio and achieved a detection accuracy of up to 99.73% using a pixel number observable. Building on such advancements, several studies further explored GNSS-R for sea ice detection and classification. Alonso-Arroyo et al. (2017) developed an algorithm using U.K. TechDemoSat-1 (TDS-1) data, detecting sea ice presence with a probability of 98.5% by comparing the received waveforms to a coherent reflection model. The study applied three estimators and found the matched filter approach to be the most effective due to its simplicity. Zhu et al. (2017) proposed two new methods, named power-summation of differential Delay-Doppler Maps (PS-D) and pixel-number of differential Delay-Doppler Maps (PN-D), for detecting sea ice using differential DDMs, which measured the degree of difference between two DDMs to distinguish between ice and water, achieving detection probabilities of 99.72% and 99.69%, respectively, with low false detection rates.

In addition to sea ice detection, Rodriguez-Alvarez et al. (2019) expanded on the application of GNSS-R by classifying sea ice types during the formation period in the Arctic. Using TDS-1 data, they developed a multi-step classification approach to distinguish between

young ice, first-year ice, and multi-year ice with success rates of 70%, 82%, and 81%, respectively, demonstrating GNSS-R's sensitivity to different surface scattering properties of ice types. Cartwright et al. (2019) introduced a new sea ice detection method using TDS-1 data, which quantified the spread of power in delay and Doppler axes to differentiate between ice and open water. Their algorithm achieved over 96% accuracy in both the Arctic and Antarctic, showcasing its potential for tracking seasonal and multiyear changes in sea ice distribution. Further advancing the field, Rodriguez-Alvarez et al. (2023b) processed Stokes and child Stokes parameters from SMAP-R signals to study sea ice cover changes, finding that polarimetric parameters, particularly S1, were highly sensitive to the presence of sea ice, with a correlation of 77.2% for S1 and 70% for the ellipticity parameter (χ).

Machine learning approaches have been increasingly applied to improve the accuracy of sea ice detection and sea ice concentration (SIC) estimation using GNSS-R data. Yan et al. (2017) introduced a neural network (NN) scheme using multilayer perceptron neural networks with back-propagation learning for sea ice detection and SIC retrieval from GNSS-R DDMs. Their approach achieved a detection accuracy of 98.4% and a correlation coefficient of 0.93 for SIC estimation, although low sea state and wind speed led to overestimation in some cases. Building on this, Yan and Huang (2018) proposed a convolutional neural network (CNN) scheme for sea ice detection and SIC prediction. In this study, CNNs achieved a sea ice detection accuracy of 98.9%, surpassing NNs, especially when DDM data were not preprocessed. However, when the data were adequately preprocessed, both CNNs and NNs achieved similar accuracy levels for SIC estimation, with a correlation coefficient of 0.94. Lastly, Hu et al. (2023) employed a residual neural network (ResNet) to address the challenges of noise and accuracy reduction during the sea ice melting period. Their method, applied to TDS-1 data, achieved a high detection accuracy of 98.61% and

demonstrated strong robustness to noise and stability during melt periods, outperforming other sea ice detection algorithms.

Furthermore, over the Greenland ice sheet, researchers have conducted GNSS-R experiments utilizing different GNSS-R platforms. Rius et al. (2017) demonstrated the feasibility of GNSS-R for ice sheet altimetry in Greenland using TechDemoSat-1 (TDS-1) data, achieving an average difference of 4.6 meters when compared to ICESat GLAS altimetry data. Despite these differences, their results showed GNSS-R's capability for monitoring ice sheet topography with sufficient accuracy to complement existing radar altimetry methods. Li et al. (2020) explored GNSS-R's capability for detecting ice sheet melt in Greenland, focusing on the sensitivity of GNSS-R to liquid water presence in the snowpack. This study found a 90% agreement between GNSS-R and microwave radiometer data for detecting melt during the 2018 season, with GNSS-R detecting melt in 37% of cases where the radiometer did not, due to the larger penetration depth of GNSS-R signals into the ice sheet subsurface. Buendia et al. (2023) took a different approach by using grazing angle GNSS-R observations from Spire Global CubeSats to retrieve ice sheet surface heights in Greenland. Their study processed over 7,800 coherent segments and achieved a root mean square error of approximately 1.7 meters, demonstrating the potential of grazing angle GNSS-R observations for accurately measuring ice sheet heights. Recently, Rodriguez-Alvarez et al. (2023b) identified reflectivity increases of 4.8 dB (30% change) during the melt season, particularly near the coastal area where the melt is most prominent. In addition, polarimetric parameters S_2 and δ correlated with ice sheet thickness (thickness < 2 km, with correlations of up to 50%.

GNSS-R has also been effectively used to monitor the freeze/thaw (F/T) state of soils, offering valuable insights into seasonal transitions in high-latitude regions. Using SMAP-R data,

Chew et al. (2017) demonstrated the potential of GNSS-R to detect soil F/T transitions within boreal wetlands, showing a significant ~10 dB difference in signal-to-noise ratio (SNR) between frozen and thawed states. This study highlighted the ability of GNSS-R to monitor these transitions at kilometer-scale resolution. Comite et al. (2020) further investigated the use of GNSS-R from TDS-1 for F/T monitoring, comparing reflectivity values with SMAP freeze/thaw data and in situ soil temperature measurements across Siberia, Finland, Canada, and Alaska. They confirmed a decrease in reflectivity for frozen soils and an increase for thawed soils, demonstrating a dynamic range up to 10 dB. However, the study also noted challenges such as calibration issues, vegetation interference, and water body effects. Rautiainen et al. (2021) advanced GNSS-R's application for F/T detection in high-latitude regions, comparing TDS-1 reflectivity values with SMOS data. Their study demonstrated a dynamic range of 2-7 dB for different land covers and elevations, confirming GNSS-R's sensitivity to F/T dynamics in Siberia and Finland. In an expanded study, Carreno-Luengo and Ruf (2022) developed a Seasonal-Threshold Algorithm (STA) using CYGNSS data to retrieve F/T surface states in South America. Their results showed a classification accuracy of 84.2% for F/T detection when compared with SMAP F/T products and ERA5-Land data. The study found that CYGNSS provided improved spatio-temporal resolution, particularly in mountainous and remote regions. The algorithm successfully captured freeze events with a probability of detection of 89%, while the false alarm rate was limited to 10%. These findings emphasize the potential of CYGNSS for enhancing F/T detection in challenging environments. Rodriguez-Alvarez et al. (2024) employed SMAP-R signals to classify the F/T state over the Northern Hemisphere, applying a Random Forest algorithm to improve classification accuracy. Their results showed an agreement of over 97% with official SMAP F/T products, proving the efficacy of GNSS-R for F/T monitoring in polar regions.

The use of space-borne GNSS-R systems for remote sensing of lake ice properties remains very limited. Mayer and Ruf (2018) first proposed employing the CYGNSS constellation for altimetry over lake ice, proposing the potential for measure ice thickness by leveraging the transparency of GNSS L-band signals through the ice surface. Qinghai Lake, situated on the Tibetan Plateau, became the first location where a study on CYGNSS altimetry confirmed the presence of lake ice during the winter of 2018 (Li et al., 2018). Zavorotny et al. (2020) further analyzed raw data from three specular tracks over Qinghai Lake to assess the coherence of scattered signals under both open water and frozen conditions. Their findings showed that the Fresnel reflection coefficient of the ice was lower than that of lake water, resulting in greater fluctuations in SNR reflected from the ice. These fluctuations were further influenced by the interference of signals reflected from both the top and bottom of the ice, alongside variations in ice surface roughness (Zavorotny et al., 2020). This thesis expands on these findings, further investigating the potential of GNSS-R for lake ice detection and phenology analysis with also an examination of scattering mechanisms with ice properties.

2.3. Scattering Mechanisms of Lake Ice

The microwave scattering mechanisms of lake ice have been extensively studied using active microwave remote sensing techniques, such as synthetic aperture radar (SAR) and radar altimetry, yet they remain largely unexplored for GNSS-R. This section first provides an overview of the active microwave scattering mechanisms of lake ice for SAR, the most prevalent microwave remote sensing technique for lake ice monitoring. Subsequently, necessary modifications are applied to extend these principles and better understand the scattering mechanisms of lake ice for GNSS-R.

2.3.1. Imaging SAR Remote Sensing of Lake Ice

The size of a target detected by a radar system depends on its frequency and wavelength, as well as the properties of the medium through which the radar signal travels. For lake ice, different frequencies have shown sensitivity to monitor different ice features and properties, such as bubble size/density, fractures, and interface roughness. An essential control on microwave signal response to lake ice is the dielectric constant (or relative permittivity, ϵ_r), which can be calculated using permittivity (ϵ') and dielectric loss (ϵ'') through the following equation (Ulaby et al., 2014):

$$\epsilon_r = \epsilon' - j\epsilon'' \quad (2 - 7)$$

A signal's penetration depth is also determined by its frequency and wavelength. Equation 2-8 is used to calculate the penetration depth (δ_p) in freshwater ice where $\epsilon'' \ll \epsilon'$ (Ulaby et al., 2014).

$$\delta_p \approx \sqrt{\epsilon'}/(k_0\epsilon'') \quad (2 - 8)$$

where k_0 is the wavenumber in free space. The penetration depth in pure ice from 100 MHz to 100 GHz is presented in Figure 2-5, showing that 30 GHz or below is the best frequency range for microwave sensors to receive signals from ice, as this guarantees that the signals are affected by ice properties.

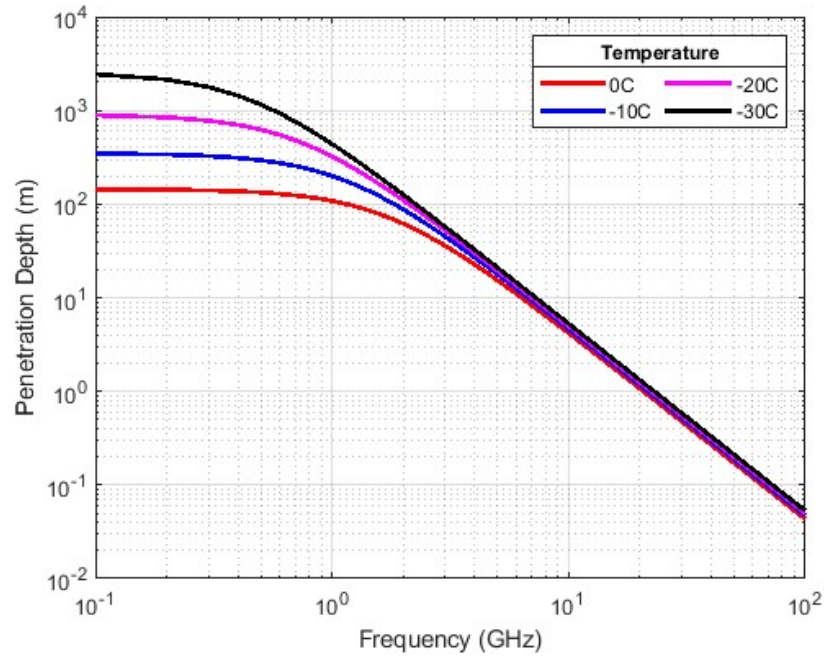


Figure 2-5. Penetration depth for pure ice for 100 MHz to 100 GHz frequencies from temperatures ranging from 0 to -30°C. Penetration depths calculated from Equation 2-8 (Ulaby et al., 2014).

Although the study areas of this thesis are all large lakes, all studies done so far for backscatter mechanisms have been conducted over small and shallow lakes. Therefore, we provide these details here, which specifically pertain to shallow lakes. Studies investigating lake ice properties from active microwave use data acquired at Ku-band (17.2 GHz), X-band (9.6 GHz), C-band (5.4 GHz), and L-band (1.27 GHz) frequencies.

High and low backscatter values from lakes can be observed on days before freeze-up due to scattering off the rough lake surface. In Arctic latitudes, these changes have been recorded in studies using X-, C-, and L-band frequencies over various Arctic and sub-Arctic lake conditions, including floating ice and bedfast (Jeffries et al., 2012; Duguay et al., 2002). Morris et al. (1994) also included Ku-band to evaluate the backscatter range from deep Arctic lakes with floating ice. Once the first skim ice forms, the ice-water interface becomes smooth, acting as a specular

reflector and reducing backscatter (Duguay et al., 2002). However, fractures or deformations during ice formation can increase backscatter by up to 10 dB (Morris et al., 1994). As ice thickens, backscatter decreases when it reaches the lakebed, supported by experiments using X-, C-, and L-bands (Antonova et al., 2016; Engram et al., 2013).

Backscatter declines in the spring as snow melts and water pools on the ice surface, increasing water content (Duguay et al., 2002). In shallow lakes in Alaska, L-band returns were influenced by surface roughness, decreasing as ice grounded on the lakebed (Engram et al., 2013). Methane bubbles trapped in ice also contributed to surface scattering, with higher backscatter in lakes with more bubbles (Engram et al., 2013). Even without bubbles, backscatter at the ice-water interface was significantly higher when minor roughness was present, supported by TerraSAR-X, ALOS PALSAR, and RADARSAT-2 data (Atwood et al., 2015). These scattering mechanisms are shown In Figure 2-6; however, further research is needed to determine if the backscatter in deeper lakes increases over the ice season as a result of the ice-water interface roughness or if there are other variables (Murfitt and Duguay, 2021).

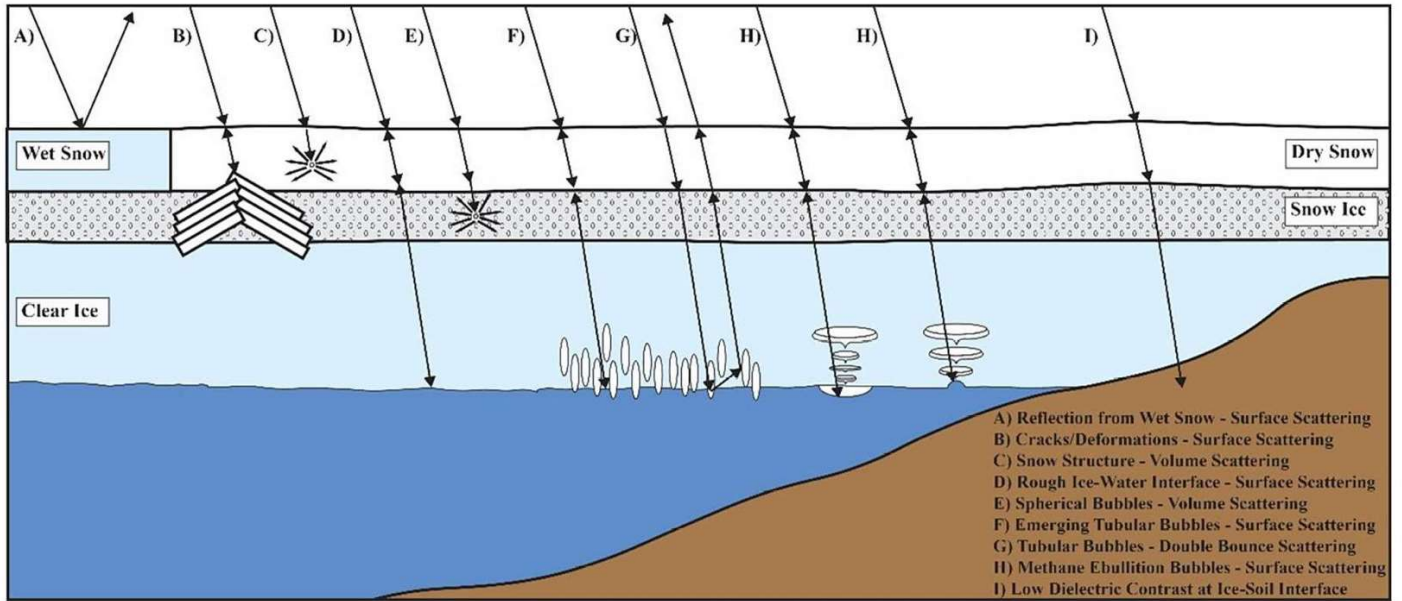


Figure 2-6. Scattering mechanisms for Ku-, X-, C, and L-band frequencies. (from Murfitt and Duguay, 2021)

2.3.2. Lake Ice Scattering Mechanism for GNSS-R

In the context of GNSS-R, the scattering mechanism of lake ice introduces unique characteristics to the reflected GNSS signals. Given that GNSS signals operate in L-band, with a wavelength of approximately 19 cm, the penetration depth into freshwater ice can be significant, potentially reaching up to 100 meters, as shown in Figure 2-5. However, this penetration depth is highly dependent on the salinity; as salinity increases, the loss factor also increases, which, in turn, reduces the penetration depth. This highlights the importance of considering the dielectric properties of the lake ice when analyzing GNSS-R signals.

The L-band wavelength is also larger than the typical size of snow and ice particles, which results in negligible volume scattering from the snow and snow-ice layers. This is in contrast to what might be observed with shorter wavelength signals, such as those in the Ku-band, where volume scattering is more prominent, as depicted in scenarios C and E of Figure 2-6.

The scattering mechanism for GNSS signals is dominated by forward scattering. This reflection is directed towards the GNSS receiving antenna, forming the basis of GNSS-R measurements. When considering lake ice as the target of GNSS-R, the primary reflection mostly occurs at the ice-water interface. However, additional reflections may occur under specific conditions, such as when there is wet snow/ice or when the ice surface has cracks or deformation (Scenarios A and B in Figure 2-6). These factors introduce complexities in the scattering mechanism, potentially leading to multiple reflection interfaces that can affect the coherence and strength of the reflected signals. More details on the GNSS-R scattering mechanism of lake ice will be provided in Chapter 5.

2.4. Advantages and Challenges of GNSS-R for Lake Ice Cover Monitoring

The first and most notable advantage of GNSS-R over other microwave sensors is the low cost of instrumentation as, similar to other SoP systems, no transmitter is required. Furthermore, thanks to the growing number of operational GNSS satellites and the increased number of channels in which modern GNSS-R space missions operate, each pass may consist of tens of tracks covering several targets on the Earth based on the orbital geometry of transmitters and receivers. For instance, the CYGNSS constellation consists of eight LEO microsatellites, each operating at four channels, i.e., each antenna receives reflections from four GPS satellites at the same time, resulting in 32 observations, in total, from different regions at each sampling epoch. This increases the density of observations, allowing researchers to have access to a larger number of measurements and, in turn, fewer uncertainties.

In most previous research, the GNSS-R experiments have been limited to single-scattering regimes, i.e., there is only one reflective layer. This simplifying assumption works properly for GNSS-R experiments over first year sea ice because the loss factor is high and, as a consequence, the penetration depth for L-band signals is so low that one can assume there is no reflection from the ice-water interface (Ulaby et al., 2014). However, this assumption for lake ice may not be accurate since the dielectric properties of lake ice allow L-band signals to penetrate up to hundreds of meters; therefore, it is anticipated to have a reflection from the underlying surfaces as well. This would make the search for the BRCS substantially more difficult (finding the BRCS is already complicated even for the simpler situation of a single-scattering regime). Furthermore, the surface approximations in most GNSS-R missions are based on ocean scatterometry. Most scattering models from a rough surface, such as KA-GO, would lead to an incorrect result in case of weak diffuse scattering, which is a common case in lake ice studies. Although small-slope approximation (SSA) has been proposed by Voronovich and Zavorotny (2017b) for the case of weak diffuse scattering, its validity under a multi-scattering regime such as freshwater ice is yet to be investigated.

Chapter 3 - Potential of GNSS-R for the Monitoring of Lake Ice Phenology

Abstract— This study introduces the first use of Global Navigation Satellite System Reflectometry (GNSS-R) for monitoring lake ice phenology. This is demonstrated using Qinghai Lake, Tibetan Plateau, as a case study. Signal-to-Noise Ratio (SNR) values obtained from the Cyclone GNSS (CYGNSS) constellation over four ice seasons (2018 to 2022) were used to examine the impact of lake surface conditions on reflected GNSS signals during open water and ice cover seasons. A moving t-test algorithm was applied to time-varying SNR values allowing for the detection of lake ice at daily temporal resolution. Good agreement was achieved between ice phenology records derived from CYGNSS data and Moderate Resolution Imaging Spectroradiometer (MODIS) imagery. The CYGNSS timings for freeze-up, i.e., the period starting with the first appearance of ice on the lake (freeze-up start; FUS) until the lake becomes fully ice covered (freeze-up end; FUE), as well as those for breakup, i.e., the period beginning with the first pixel of open water (breakup start; BUS) and ending when the whole lake becomes ice-free (breakup end; BUE), were validated against the phenology dates derived from MODIS images. Mean absolute errors are 7, 5, 10, 4 and 5 days for FUS, FUE, BUS, BUE and ice cover duration, respectively. Observations revealed the sensitivity of GNSS reflected signals to surface melt prior to the appearance of open water conditions as determined from MODIS, which explains the larger difference of 10 days for BUS.

Index Terms— Global Positioning Satellite System Reflectometry (GNSS-R), Cyclone GNSS (CYGNSS), Lake Ice, Phenology, Qinghai Lake.

3.1. Introduction

The seasonal cycle and duration of lake ice cover, which involves the time between freeze-up and breakup periods, is described by ice phenology (Duguay et al., 2003). Freeze-up covers the period between freeze onset (the first appearance of ice) and when a complete ice sheet covers the lake surface, often referred to as freeze-up start (FUS) and freeze-up end (FUE), respectively. Similarly, breakup corresponds to the period between the first appearance of open water and full disappearance of ice from the lake surface (Duguay et al., 2003), also commonly known as breakup start (BUS) and breakup end (BUE), respectively. The presence/absence and extent of ice cover and ice thickness as well as freezing duration (FD) and breaking duration (BD) during winter months have wide-ranging impacts on lake-atmosphere interactions, e.g., lake-effect snowfall, thermal moderation (e.g., Brown and Duguay, 2010), aquatic ecosystems (Mishra et al., 2011), and human activities ranging from winter transportation and hydroelectric power generation to ice skating and religious ceremonies (Knoll et al., 2019). Lake ice cover and thickness have been noted as sensitive indicators of climate change and, as such, are identified as thematic products of lakes as an essential climate variable (ECV) by the Global Climate Observation System (GCOS, 2022a; 2022b). Recent long-term trends in lake ice phenology for northern lakes show an average shortening of ~17 days in the duration of ice over the last century (Sharma et al., 2021). Analyzing lake ice phenology records from 1855 to 2019, Sharma et al. (2021) found that freeze-up has been occurring, on average, ~11 days later, while breakup has been starting ~7 days earlier per century. While ground-based observational sites have provided much of the evidence for changes in ice phenology (e.g., Benson, 2013), the number of sites has dwindled in the last 40 years (Duguay et al., 2015; Murfitt and Duguay, 2021). In this respect, satellite remote sensing is playing an

increasingly important role in monitoring lake ice phenology and documenting recent changes (Duguay et al., 2015; Hall and Riggs, 2021; Wu et al., 2021; Cai et al., 2022).

Satellite remote sensing of lake ice cover is either based on the use of optical, passive microwave, or active microwave data, each presenting some advantages and limitations (Murfitt and Duguay, 2021). Among the data sources, those from optical remote sensing satellite missions are available with extended time series (ca. 20 years for MODIS and ca. 40 years for Landsat) and at varying resolutions (ca. 30 m for Landsat and ca. 500 m for MODIS); however, the quality of the ice phenology records from these data is impacted by the presence of cloud cover and low solar illumination conditions/darkness. Passive microwave instruments are not influenced by the latter but, due to the low spatial resolution they provide (tens of km footprints, interpolated onto ca. 3-10 km grids), ice phenology can be retrieved from very large lakes only (Cai et al., 2022; Du et al., 2017; Kang et al., 2014). While active microwave sensors, such as synthetic aperture radar (SAR), can also operate under all-weather and light conditions, and are increasingly providing better historical records at relatively high temporal resolution for high-latitude lakes (e.g., 1-2 days for Sentinel-1; Murfitt and Duguay, 2020), their instrumentations tend to be costly for finer temporal and spatial resolutions due to complicated board designs and high-power demands (Younis et al., 2003). Meanwhile, Global Navigation Satellite System Reflectometry (GNSS-R), as an active-passive microwave tool, is a novel remote sensing technique at a low cost that provides high temporal and spatial resolutions for a variety of ocean and land applications (Zavorotny et al. 2014). GNSS-R is a remote sensing technique based on receiving and processing reflected navigational L-band signals from sea and land. Hall and Cordy (1988) proposed the use of reflected GNSS signals as a bistatic radar technique for the first time, which was later followed by Martín-Neira (1993) who presented the idea of ocean altimetry using GNSS-R.

GNSS-R has been proposed and used for various applications in cryosphere remote sensing as part of ground-based, aerial, and spaceborne platforms. The use of GNSS-R for ice remote sensing was first demonstrated by Komjathy et al. (2000) with an airborne receiver for sea ice detection. Proceeding this experiment, several ground-based GNSS-R experiments for ice remote sensing have been conducted. Among them, Fabra et al. (2010), and later, Semmling et al. (2019) accomplished ground-based experiments to study sea ice concentration by analyzing signal polarization ratios. Ground-based GNSS-R is among the multiple sensors that were deployed during the Multidisciplinary drifting Observatory for the Study of Arctic Climate (MOSAiC) expedition to monitor sea ice properties (e.g., Munoz-Martin et al., 2020). Jacobson (2010; 2015) proposed the potential of GNSS-R for estimating lake ice thickness (LIT), a concept that was further explored by Ghiasi et al. (2020) at sub-Arctic lake ice sites and achieved average errors of 0.07 m in LIT retrievals when compared to manual measurements (drilled holes with auger in the ice). Several space-based GNSS-R experiments have also been carried out for sea ice detection using data acquired by the UK-DMC and TDS-1 satellites. Moreover, two recent spaceborne GNSS-R missions, namely Spire and FSSCat (Federated Satellite Systems/3Cat), have shown potential for sea ice characterization, including ice concentration and ice type as well as sea surface height (Jales et al., 2020; Nguyen et al., 2020; Llaveria et al., 2021).

Few studies have explored signals recorded by spaceborne GNSS-R systems to detect or monitor lake ice properties. One GNSS-R spaceborne platform with potential for lake ice monitoring is the Cyclone GNSS (CYGNSS) constellation system. It is the first GNSS-R pathfinder mission consisting of eight Low Earth Orbiting (LEO) micro-satellites. CYGNSS was launched in December 2016 with the main objective of monitoring near-surface ocean wind and currents monitoring (e.g., Carreno-Luengo et al., 2021; Asgarimehr et al., 2020; Hoseini and

Nahavandchi, 2022); however, it can also be used as a remote sensing tool for remote sensing of other environmental characteristics, including, but not limited to, inland water monitoring (e.g., Ruf et al., 2018; Rajabi et al., 2020; Kossieris et al., 2023), soil moisture, wetlands, and biomass observation (Rahmani et al., 2022; Morris et al., 2019; Carreno-Luengo et al., 2019), freeze/thaw state retrieval (Carreno-Luengo et al., 2021; Carreno-Luengo and Ruf, 2021), and mesoscale ocean eddies observations (Hoseini et al., 2019). Mayer and Ruf (2018) proposed the potential of CYGNSS for conducting altimetry over lake ice and using the transparency of ice to GNSS L-band signals to infer ice thickness. Li et al., (2018) found the first evidence of freshwater ice effects on CYGNSS altimetry over Qinghai Lake, Tibetan Plateau, during winter 2018, by observing a lower water level during the ice season. Recently, Zavorotny et al. (2020) used CYGNSS raw data collected from three specular tracks over Qinghai Lake to investigate the scattering coherency of the lake in both open water and frozen states. The latter research suggested higher variability in the signal-to-noise ratio (SNR) reflected from the ice compared to that of open water due to the lower Fresnel reflection coefficient of the ice layer compared to the surface water. In addition, the authors considered the interference between signals reflected from the top and the bottom of the ice, as well as changes in surface roughness and ice thickness within a specular track as other parameters leading to the larger SNR fluctuation.

The primary objective of this study was to develop and evaluate an approach for the determination of lake ice phenology through the application of changes in CYGNSS SNR values. To this end, SNR values from CYGNSS level-1 data were extracted over Qinghai Lake (Tibetan Plateau, China) from August 2018 to August 2022, encompassing four ice seasons. The paper is organized as follows: the study area is briefly introduced in section 3.2, the main data set along with auxiliary data, as well as the methodology are explained in section 3.3, results and discussion

are presented in sections 3.4 and 3.5, respectively, and conclusions and prospects are drawn in section 3.6.

3.2. Study Area

The largest lake that forms a complete ice cover within the area covered by CYGNSS ($\pm 38^\circ$ in latitudes) is Qinghai Lake (Figure 3-1). The lake is located in the northeast part of the Tibetan Plateau (Lat: $36^\circ 32'$ to $37^\circ 15'N$, Lon: $99^\circ 36'$ to $100^\circ 47'E$) at an altitude of 3,260 m above sea level. Qinghai Lake is amongst the most noticeable lakes on the Tibetan Plateau and has been a lake of interest in several previous investigations, including, but not limited to, lake ice phenology, animal species living in the area, and tourism (Qi et al., 2020). Therefore, the lake was chosen as the best candidate to examine the capability of CYGNSS to monitor lake ice phenology.

Qinghai Lake has a convex shape with a tortuous coastline and contains two small islands. The lake is the largest inland waterbody of the Tibetan Plateau, filled with weakly saline-alkaline water (salinity=15.18 g/l; pH=9.2) (Dong et al., 2011). The average area of Qinghai is 4,300 km² with an average depth of 18.3 m and maximum of 26.6 m. The annual average temperature is 0.5 C (Dong et al., 2011). In Qinghai Lake, the freeze-up period usually begins in mid-December and lasts until early January. The breakup period starts during the second half of March and ends in early April (Qi et al., 2019).

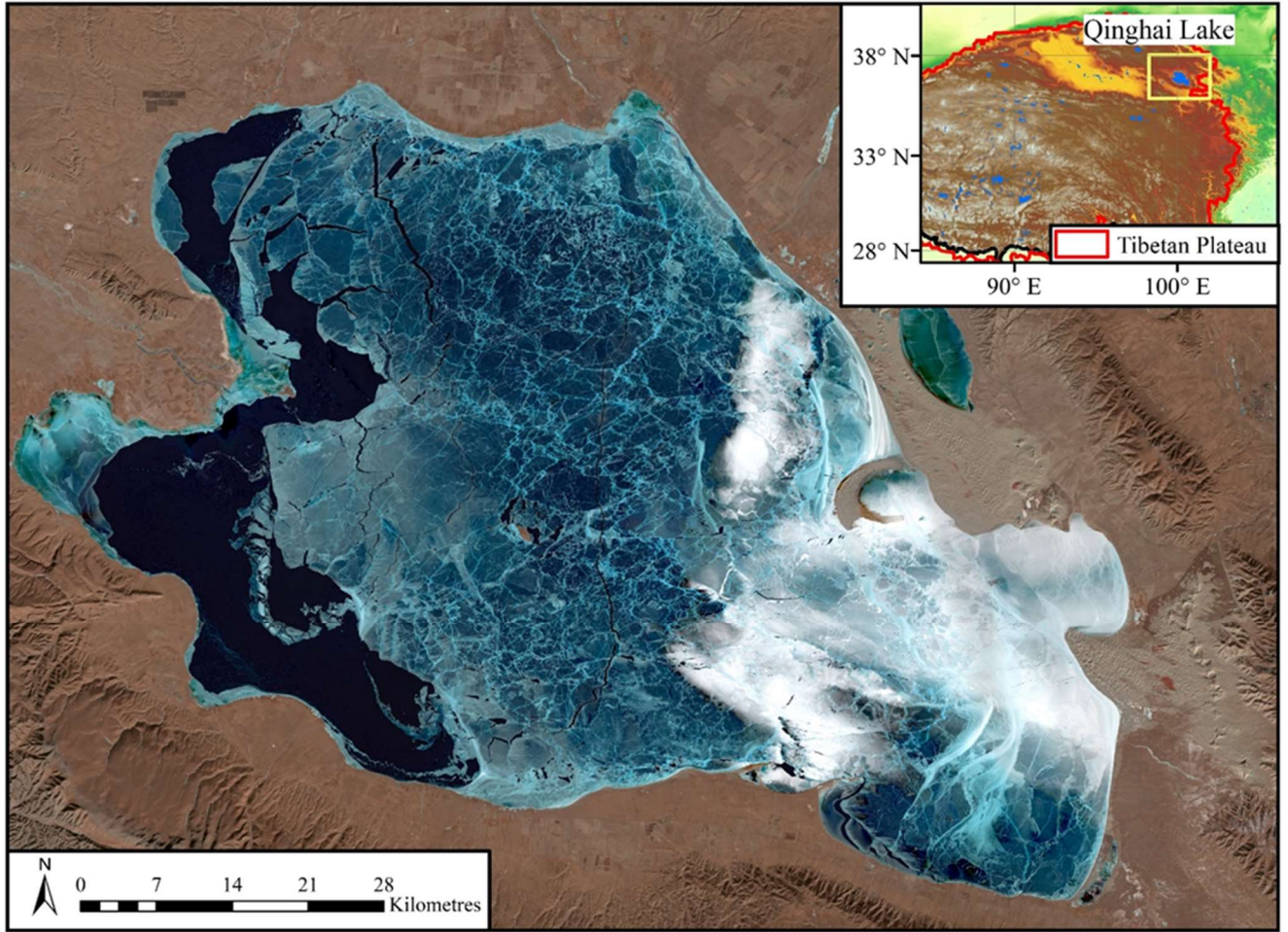


Figure 3-1. Location of Qinghai Lake on the Tibetan Plateau. Landsat-8 Level-1 OLI/TIRS image courtesy of the United States Geological Survey (USGS) Digital Object Identifier (DOI) number: /10.5066/F71835S6. Topographic is also courtesy of the USGS, GTOPO30 Hydro1K, DOI number: /10.5066/F77P8WN0.

3.3. Data and Methods

3.3.1. CYGNSS Data

The main data product of CYGNSS are delay-Doppler maps (DDMs), which are the cross-correlation power of the forward scattered signal with its replica generated locally at the receiver, in a range of delay and Doppler frequency shifts. Radar observables can be extracted from the DDMs and are stored as metadata in the CYGNSS level-1 data products. The data are available to

users in netCDF format through the Physical Oceanography Distributed Active Archive Center (PODAAC) database. More details on CYGNSS data products are provided in (Ruf et al., 2016). This study used CYGNSS level-1 version 3.0 data covering the period from 1 August 2018 to 1 August 2022, which encompasses four full ice seasons. The key observations used in this study are the SNR values of the DDMs, which have already been calculated and included amongst the CYGNSS metadata. Due to the high temporal revisit of the CYGNSS constellation, with an average revisit time of 7 hours, 117,190 specular points were obtained from 7,140 specular tracks. Over the four ice seasons of this study, the average number of footprints per day was 62 (maximum 260 and minimum 1), which were collected through, on average, two daily specular tracks over the lake. The average SNR values were then calculated with an average variance of 0.05 for each day. Average daily SNR values were used to analyze the impact of surface conditions on SNR and determine ice phenology.

Low signal-to-noise ratio (SNR) measurements are frequently encountered on land, which can be attributed to either the specular point's position within the CYGNSS antenna pattern or a minimal amount of surface scattering (Al-Khaldi et al., 2019). Consequently, it is crucial to exclude measurements with low SNR from the time series retrieval process because they exhibit inferior measurement quality. Therefore, observations with SNR values below zero are also excluded.

3.3.2. Moderate Resolution Imaging Spectroradiometer (MODIS) Images

MODIS true color composite (Red= band 1, Green= band 4, and Blue= band 3; Gumley et al., 2003) images were used to visually determine dates associated with the freeze-up and breakup periods which were compared to the dates obtained from CYGNSS. In MODIS RGB images, the freeze-up period was identified as the first date where the ice cover was visible (FUS) until the

first date when the ice cover fully covered the lake surface (FUE). The breakup period was identified as the period between the date of the first appearance of water (BUS) and the full disappearance of the ice cover from the lake (BUE). Next, the difference between FUS, FUE, BUS, and BUE dates determined from MODIS and CYGNSS was compared by calculating the mean bias error (MBE) and the mean absolute error (MAE). Ice cover duration (ICD), which is the date from the FUE to the BUE periods, as well as freeze-up duration (FD) and break-up duration (BD), were also calculated. It is worth noting that the reliability of MODIS images is influenced by the presence of clouds, and this introduces some uncertainty in the precise visual determination of the phenology dates. Considering the utilization of both Terra and Aqua images, the average frequency of cloud cover in MODIS images during FUS, FUE, BUS, and BUE periods were 2 days over Qinghai Lake, which caused 2 days uncertainty in the determination of timing of ice phenology.

3.3.3. MODIS Derived Products

In addition to MODIS color composite images, three MODIS-derived geophysical products were obtained to provide further evidence of the sensitivity of CYGNSS SNR values to lake surface conditions and to determine ice phenology. Land surface temperature (LST; MOD/MYD11A1, daily, level 3, version 6) and surface albedo (MOD/MYD10A1, daily, level 3, version 6), which are both also retrieved over inland waterbodies, were downloaded from the NASA Land Processes Distributed Active Archive Center (LP DAAC). LST and surface albedo have been found to be useful complements in the interpretation of changes in lake surface conditions during the freeze-up and breakup periods, and the development of an ice phenology retrieval algorithm from spaceborne scatterometer observations (Howell et al., 2009).

LST data was processed by averaging day and night observations from both Terra and Aqua over the entire lake for each day. According to previous validation efforts conducted by Coll

et al. (2009) and Hulley et al. (2011), MODIS LST products have shown a bias of less than 1 K compared to in-situ measurements with a mean difference of 0.27 K against ground-based LST data obtained over the Tibet Plateau (Wang et al., 2007). MODIS LST have been shown to be a reliable data source for quantifying climate variability, monitoring lake surface water temperature, and detecting lake ice over Tibetan lakes (Zhang et al., 2014; 2021). Daily LST data were used in support of the interpretation of seasonal drops and increases in SNR values with freeze-up and break-up (Sections 3.4.1 and 3.4.2).

MODIS daily albedo products were used in concert with minimum, mean, and maximum surface temperatures derived from ERA5-Land hourly data (Section 3.3.4) to detect the beginning of snow/ice surface melt before the first appearance of open water (i.e., BUS). The albedo products are generated only for clear-sky dates and snow-covered surfaces (Klein and Stroeve, 2002), which characterize the reflectance anisotropy of MODIS pixels at the spatial resolution of 500 m (Schaaf et al 2002; Wang et al., 2012). These data have previously been used to analyze the breakup period (Svacina 2014a; 2014b). In this paper, the average albedo for the whole lake was calculated for each day and used to determine the dates of beginning of surface melt, which are marked by a general continuous decrease in albedo until the appearance of open water (BUE). Since clear-sky conditions are not encountered on each day, the surface albedo values were compared with MODIS images and found to provide, on average, an uncertainty of one day during the melt onset period for the four ice seasons of analysis.

The third product used is the Lakes_cci dataset (version 2.02) produced as part of the Climate Change Initiative (CCI) of the European Space Agency (ESA). It is a daily product on a common harmonized grid (at $1/120^\circ$ or ca.1-km latitude-longitude) consisting of five thematic variables, including lake water level, lake water extent, lake surface water temperature, lake ice

cover, and lake water-leaving reflectance (Carrea et al., 2023). Among them, this study used the lake ice cover (LIC) thematic variable, which is mapped at the global scale based on a random forest classifier using Terra/Aqua MODIS top-of-atmosphere reflectance data (Wu et al., 2021). Here, the LIC dataset is used as a complementary source for comparison of CYGNSS SNR values against the lake surface conditions (ice/water) and evaluate the sensitivity of CYGNSS to lake ice. In the LIC dataset, each lake pixel is classified as either water (=1), ice (=2), cloud (=3) and bad/unusable data (=4). Here, we excluded those pixels flagged as 3 and 4, and only used the ones classified as water or ice. The overall classification accuracy of this data product, which uses a combination of 7 bands, has been reported to be greater than 97% (Carrea et al., 2023). However, product uncertainty increases during breakup and freeze-up periods where the mixture of ice and water increases the confusion in the classification process. To mitigate this issue, we applied a 7-day moving average to examine the sensitivity of CYGNSS SNR values to the presence of lake ice or open water. The Lakes_cci data product (version 2.02) covers up to the end of 2020. However, a third ice season that encompasses the breakup period of 2021 was added to the LIC dataset since some co-authors of this paper are also contributors to ESA Lakes_cci product. Year 2022 will only be added in a future release of the product such that three of four ice seasons could be compared with SNR values.

3.3.4. ERA5-Land Lake Ice Surface Temperature

To calculate daily minimum, mean and maximum temperatures of the lake ice surface, we obtained hourly ERA5-Land reanalysis data from the European Centre for Medium Range Weather Forecasts (ECMWF), which comprises a variety of lake related variables including temperature of the uppermost ice surface (Muñoz-Sabater et al., 2021). The spatial resolution of the ERA5-Land dataset is 9 km. Daily minimum, mean and maximum lake ice surface

temperatures slightly prior to and during the melt period were used, along with MODIS albedo data, to estimate the melt onset dates. The decrease in surface albedo is highly dependent on the melt of lake ice in spring, which is strongly controlled by surface temperature (melting versus subfreezing) (Duguay et al., 2003).

3.3.5. Determination of Ice Phenology from GNSS-R

In spaceborne GNSS-R, the primary scattering mode of interest is coherent reflection, in which the GNSS signals are reflected from extremely smooth surfaces compared to the wavelength, where mirror-like reflection is expected. In CYGNSS, in the case of coherent reflection, the glistening zone is approximately 0.5 to 1 km for a single pixel in DDM causing a constructive interference between scattered signals (Loria et al., 2018; Al-Khaldi et al., 2021). For inland targets, both coherent and incoherent reflection/scattering can dominate CYGNSS observations due to their properties, such as topography and small-scale roughness (Carreno-Luengo et al., 2019). On frozen lakes, the multilayer scattering regime is another potential source for the extinction of coherent reflection, which will be discussed in the next section. Several approaches have been suggested in previous studies to examine coherent reflection, including, but not limited to, the assessment of DDM SNR (Strandberg et al., 2017; Chew et al., 2016), DDM trailing edge slope (Alonso-Arroyo et al., 2017; Rodriguez-Alvarez et al., 2019), and DDM power spread extent (Al-Khaldi et al., 2021). In this study, we only examined the DDM SNR values to analyze the reflectivity of Qinghai Lake.

It is pertinent to note that alternative observables beyond SNR could be used in this study, including reflectivity and the Normalized Bistatic Radar Cross Section (NBRCS). These parameters have been employed in prior research for soil moisture retrievals. However, our investigation in this study was only focused on SNR for two principal reasons. First, NBRCS

calculations were not conducted for all inland specular points due to the absence of effective scattering area data in CYGNSS metadata files. Second, reflectivity, another viable parameter, exhibited notably similar patterns in our region of study; therefore, we opted to exclusively examine SNR as it does not require additional calculations as does reflectivity (Clarizia et al., 2019).

To determine lake ice phenology, a moving t-test (MTT) was employed to detect abrupt changes in the CYGNSS SNR time series by calculating the difference between the mean values of two subsamples. The MTT method, which was initially developed for abrupt change detection in climate data (Jiang and You, 1996; Xiao et al., 2007) has shown a strong ability in lake ice detection from satellite passive microwave data (Kang et al., 2014; Du et al., 2017). The temporal subsample size was chosen as 30 days to exclude possible short-term SNR changes. In other words, the 30-day subsamples were first selected, by moving, from the time series of daily SNR observations, and the t-scores were then calculated for each two consecutive subsamples, as suggested by Du et al. (2017) as follows:

$$t = \frac{\overline{x_{k2}} - \overline{x_{k1}}}{S_k \sqrt{\frac{1}{n_1} + \frac{1}{n_2}}} \quad (3 - 1)$$

where $\overline{x_{k1}}$ and $\overline{x_{k2}}$ are the mean values of each consecutive subsample, n_1 and n_2 are the size of subsamples (=30 days), and S_k is the variance factor calculated based on the variances for two subsamples (S_{k1}^2 and S_{k2}^2) as follows:

$$S_k = \sqrt{\frac{n_1 S_{k1}^2 + n_2 S_{k2}^2}{n_1 + n_2 - 2}} \quad (3 - 2)$$

Then, under the confidence level of 0.001, periods with $|t| > t_{0.001}$ were determined as dates in which abrupt changes happened. When an abrupt change is detected and the t-statistic is positive, it is considered part of the breakup period; however, if the t-statistic is negative, then it is part of the freeze-up period.

3.4. Results

3.4.1. Impact of Lake Surface Conditions on SNR Values

Figure 3-2 and Figure 3-3 present a set of examples of CYGNSS tracks along with DDM SNR variations under different lake surface conditions (open water, mix of ice and water, and fully ice-covered) during the freeze-up and breakup periods of ice season 2021-2022. Figure 3-2 reveals a decrease in SNR values as the lake transitions from open water to partially and then fully ice-covered conditions. Similarly, Figure 3-3 shows the sensitivity of SNR values to changing lake surface conditions just before and during the breakup period in spring 2022.

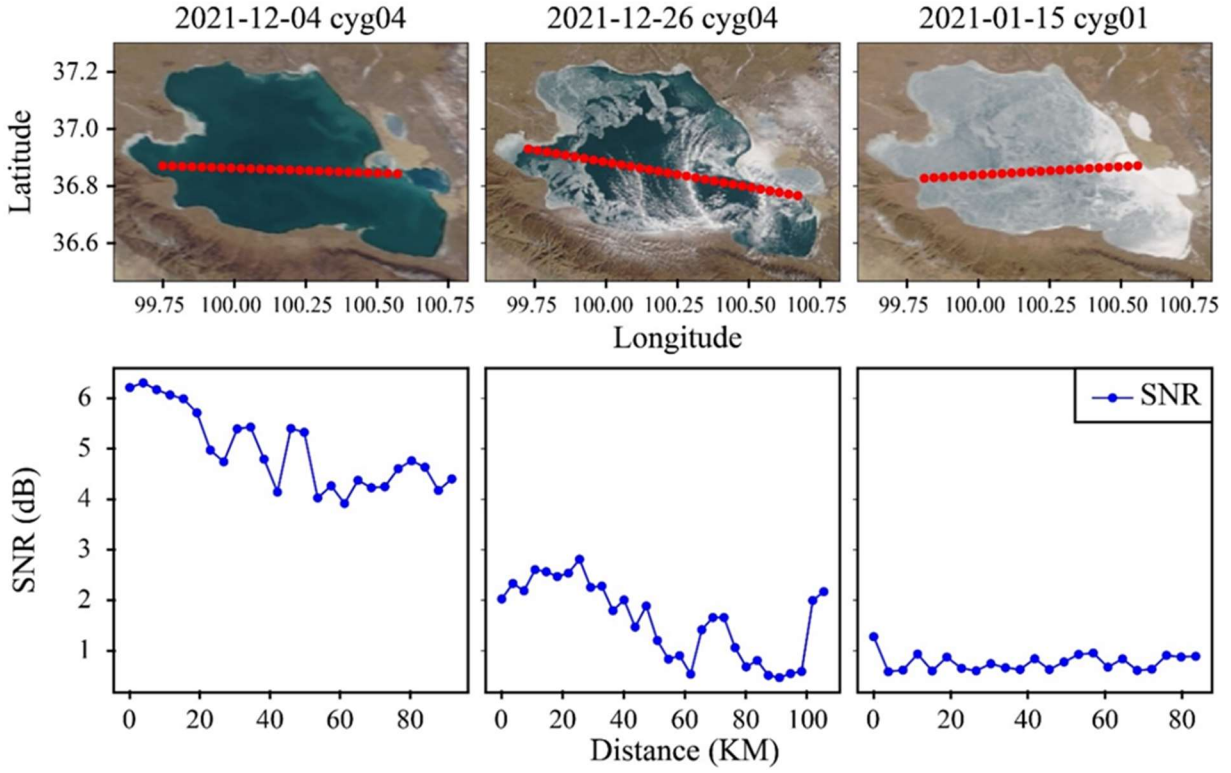


Figure 3-2. (Top) CYGNSS tracks over Qinghai Lake under three conditions: open water (left), mix of ice and water during the freeze-up period (center), and fully ice covered (right) during the 2021-2022 ice season. (Bottom) Variations in SNR along each track. The annotation cyg0# in each subplot indicates which CYGNSS satellite was used for the observation. Images courtesy: MODIS-Aqua.

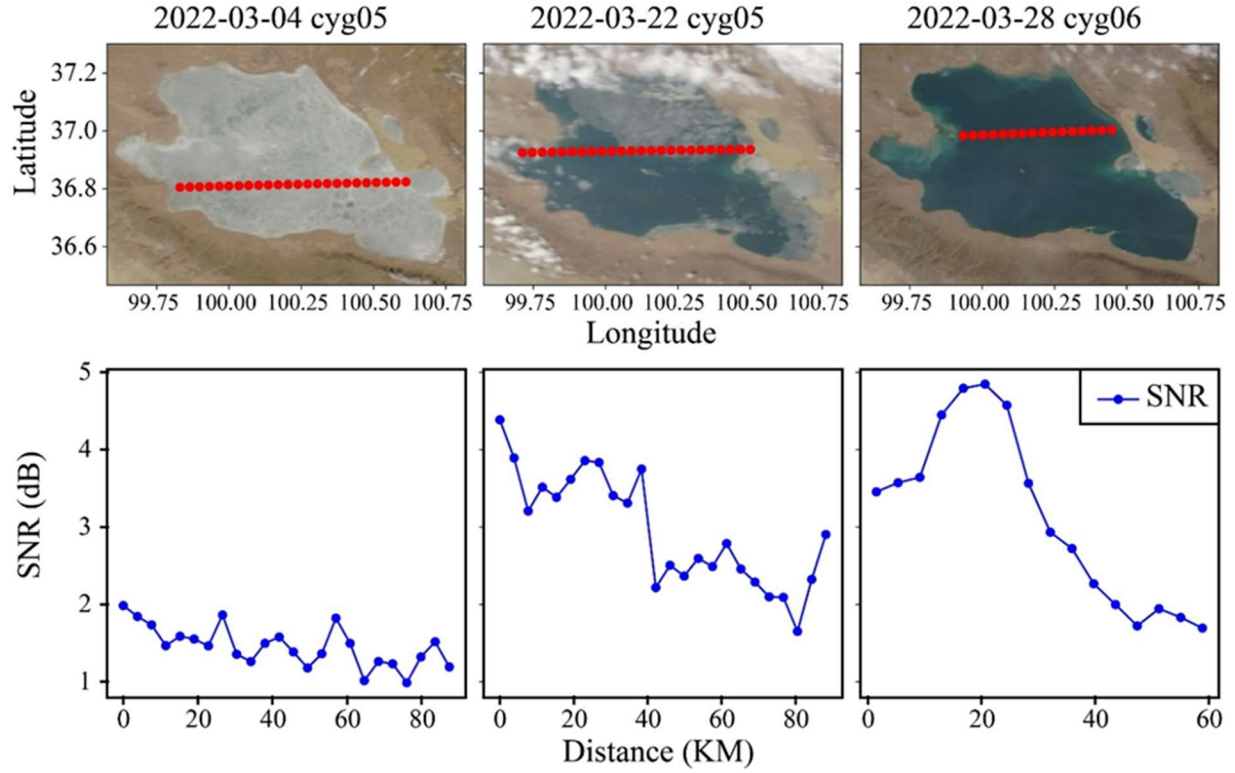


Figure 3-3. (Top) CYGNSS tracks over Qinghai Lake under three conditions: fully ice covered before breakup start (left), mix of ice and water during the breakup period (center), and open water (right) during the 2021-2022 ice season. (Bottom) Variations in SNR along each track. The annotation cyg0# in each subplot indicates which CYGNSS satellite was used for the observation. Images courtesy: MODIS-Aqua.

Figure 3-4 shows the impact of lake surface conditions during open water and ice cover seasons on reflected GNSS signals (aggregated lake-wide) over the four-year ice seasons. SNR fluctuations of the reflected GNSS signals from the lake indicate a lower reflection from ice cover and, in contrast, a higher reflection from open water. This is expected to be due to the low salinity of lake ice (12 ppt for Qinghai Lake), which results in a lower loss factor for L-band signals than, for example, first-year sea ice (Ulaby et al., 2014). The thickening of ice on the lake causes an interference between signals reflected from the ice surface and the ice-water interface; therefore, the single-scattering regime assumption suggested by Zavorotny et al. (2014) may not be

preserved, which results in significant variations in SNR values during the ice season as discussed in Zavorotny et al. (2020) and seen in Figure 3-4. Our observations during the four-year study period show that the average of CYGNSS SNR values during the ice growth period remains below 1.66 dB with standard deviation of 0.84, while it increases to 3.1 dB (standard deviation=1.4) when the lake condition is open water.

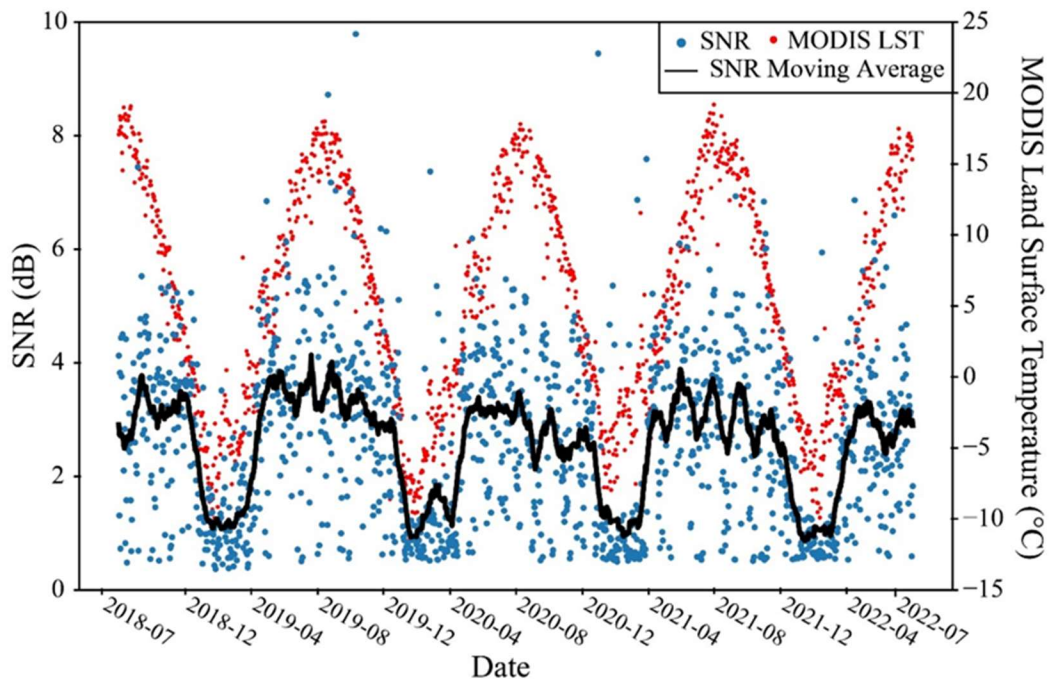


Figure 3-4. Variations in CYGNSS SNR (aggregated lake-wide) values over Qinghai Lake (light blue) with a 30-day moving average (dark blue) showing lower reflections during wintertime. MODIS LST variations are shown in dark/light red.

Furthermore, when Lakes_cci LIC data are compared with CYGNSS SNR values, there is a strong relationship between the presence of ice cover and low SNR values. Figure 3-5 displays a 7-day moving average applied to the Lakes_cci LIC data (1=water; 2=ice) along with that of CYGNSS SNR values from the whole surface of the lake. When comparing these two datasets, 86% of pixels classified as ice by Lakes_cci LIC (class 2) have SNR values below 1.66 dB, which

is the average value of CYGNSS SNR recorded during the freeze-up period. On the other hand, 82% of the SNR observations with values below 1.66 dB are from areas that are flagged as lake ice in the Lakes_cci LIC data product.

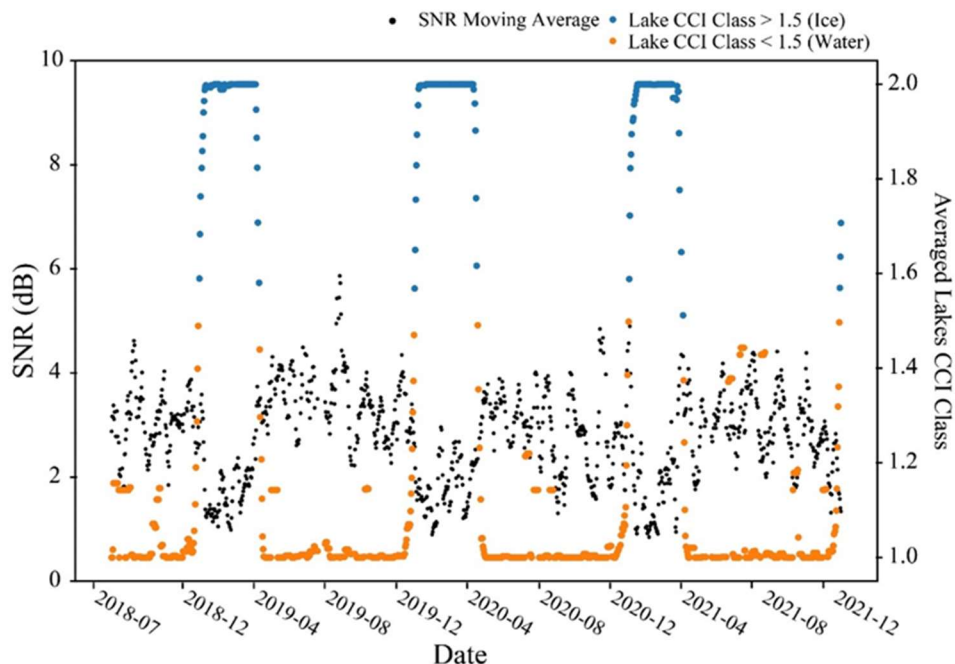


Figure 3-5. CYGNSS SNR values (blue dots) and Lakes_cci LIC classification from a 7-day moving average. Orange dots correspond to when the moving average for the LIC classification was less than 1.5 (water) and blue dots correspond to when the moving average for the LIC classification was greater than 1.5 (ice). Points where the average is greater than 1.5 likely correspond to the ice season, which matches well the drops in CYGNSS SNR values.

3.4.2. Lake Ice Phenology Determination from SNR Values

Figure 3-6 shows the SNR time series, the t-scores obtained from the MTT method, and the phenology dates determined using MODIS RGB color composite images and CYGNSS SNR analysis. In addition, Table 3-1 contains the dates associated with ice phenology and ICD derived from CYGNSS and those determined from the interpretation of MODIS RGB images from August 2018 to August 2022. Results show a generally good agreement between visually determined freeze-up and breakup periods and those dates that correspond to abrupt changes in CYGNSS

SNRs detected from the MTT method (i.e., t-scores calculated from Equation 3-2). Furthermore, the maximum absolute t-score values (MTT spike in Table 3-1) occur within the freeze-up and breakup periods visually obtained from MODIS images. This demonstrates the ability of GNSS signals to determine lake ice phenology events.

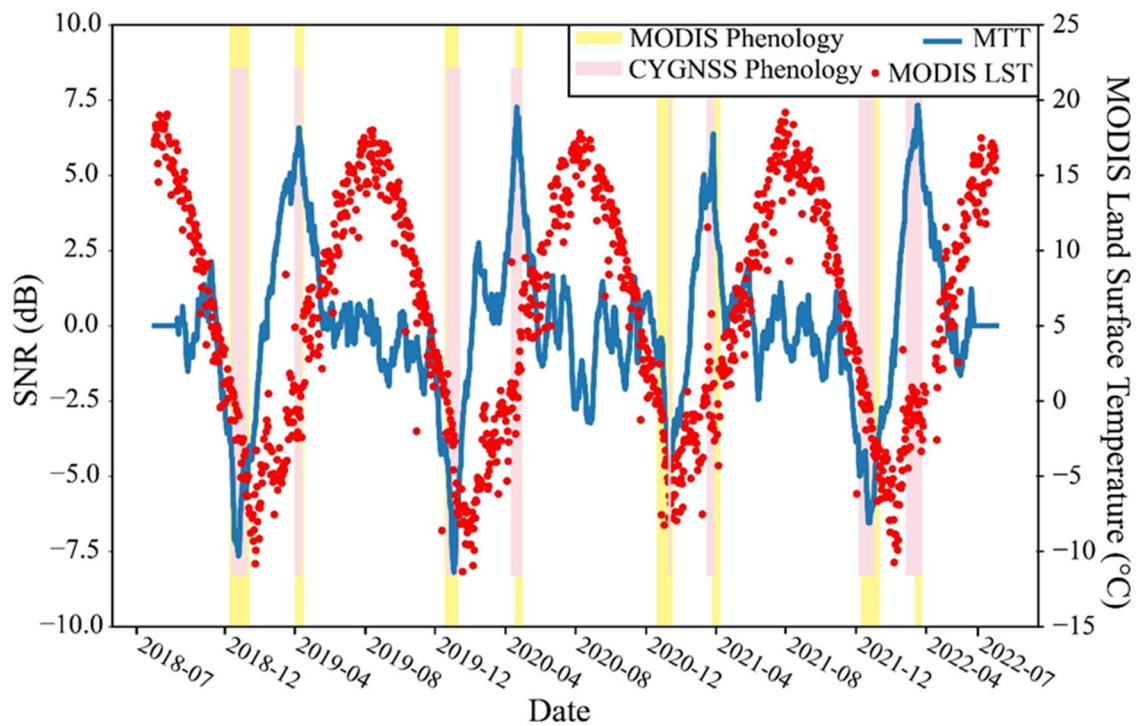


Figure 3-6. CYGNSS SNR MTT from 1 August 2018 to 1 August 2022. Pink bars are ice phenology periods obtained from CYGNSS and yellow bars are those visually determined from MODIS images over four FU and four BU periods. MODIS LST values are also plotted (red dots) to show that the timing of the FU and BU periods closely match below and above freezing temperature of 0°C, respectively.

Table 3-1. Summary of FU and BU periods, ICD, and MTT spike dates for each year from 2018 to 2022 determined from CYGNSS data and MODIS images. The first and last dates of the FU and BU periods correspond to FUS, FUE, BUS, and BUE.

	<i>2018-2019</i>		<i>2019-2020</i>		<i>2020-2021</i>		<i>2021-2022</i>	
	FU	BU	FU	BU	FU	BU	FU	BU
<i>MODIS</i>	Dec 9 – Jan 13	Apr 4 – Apr 18	Dec 18 – Jan 11	Apr 18 – May 1	Dec 20 – Jan 17	Mar 26 – Apr 9	Dec 10 – Jan 11	Mar 16 – Mar 25
<i>CYGNSS</i>	Dec 13 – Jan 9	Apr 1 – Apr 14	Dec 21 – Jan 14	Apr 10 – Apr 30	Jan 10 – Jan 12	Mar 17 – Mar 29	Dec 6– Jan 2	Feb 26 – Mar 26
<i>MTT Spike</i>	Dec 25	Apr 9	Jan 4	Apr 24	Jan 10	Mar 28	Dec 27	Mar 19
<i>MODIS ICD</i>	95 days		110 days		82 days		73 days	
<i>CYGNSS ICD</i>	95 days		106 days		76 days		83 days	

3.5. Discussion

3.5.1. Lake Ice Impact on GNSS-R Coherence

Depending on the surface roughness, the GNSS signal reflection is composed of two coherent and incoherent components. The surface roughness weakens the reflection coherency and is inversely correlated with the power. At first glance, it might be intuitively assumed that ice over the lake surface can prevent formation of waves, and therefore, due to the roughness decrease, the coherent reflection is intensified. This is a common case seen over sea, as the sea ice results in higher reflection power than sea water. However, this assumption ignores the role of the Fresnel

reflection coefficient, which in turn is controlled by the surface permittivity. The permittivity is also dependent on the salinity, which therefore suggests different behaviors over sea and lakes. Additionally, over ice, unlike liquid water, a multi-layer reflection can apply, which will lead to a decrease in the reflection power due to the interference between signals reflected from the top and bottom of the ice and by different layers. As a result, the drop in SNR over lake ice is physically plausible, and such behavior has also been documented in other lake ice studies using GNSS-R (Zavorotny et al., 2020).

According to (Loria et al., 2020), three attenuation factors can be considered for the DDM power obtained from inland targets, which are the power Fresnel reflection coefficient driven by the dielectric properties of the surface, the decorrelation factor controlled by the surface roughness, and the attenuation factor owing to vegetation canopy. In the case of lake ice, only the first two are the main factors controlling the attenuation, which are the Fresnel reflection coefficient of the reflective surface and the roughness-driven decorrelation factor. Over open water, wind-generated waves can be large enough to generate a strong diffuse scattering regime, leading to the extinction of the coherent component (Zavorotny et al., 2020). However, as the lake transitions to the frozen state, both drivers change and, as a result, the received power varies and becomes even lower than that from open water.

3.5.2. Lake Ice Phenology Analysis Accuracy

Table 3-2 contains a summary of the average differences calculated over the four ice seasons between the CYGNSS-derived ice phenology dates and those derived from MODIS images. The mean bias error (MBE) for FUS reveals that CYGNSS detects initial ice formation on average 6 days later than MODIS (mean absolute error (MAE) = 7 days). FUE, which corresponds to the date when the lake becomes fully frozen, is detected slightly earlier by CYGNSS (MBE = -

4 days; MAE = 5 days). During the breakup period, BUS is determined to occur 10 days earlier (MBE = -10 days; MAE = 10 days) and BUE slightly earlier (MBE = -4 days; MAE = 4 days) from CYGNSS than the MODIS-derived dates. The MBE and MAE of ICD obtained from CYGNSS are 0 and 5 days.

Table 3-2. Mean bias error (MBE) and mean absolute error (MAE) for FUS, FUE, BUS, BUE, and ICD between CYGNSS and MODIS

	Freeze up		Break up	
	FUS	FUE	BUS	BUE
MBE	6 days	-4 days	-10 days	-4 days
MAE	7 days	5 days	10 days	4 days
ICD MBE	0 days			
ICD MAE	5 days			

3.5.3. Sensitivity of SNR Values to Spring Melt Onset

An explanation for the larger discrepancy between CYGNSS SNR and MODIS-derived timing for the beginning of the breakup period (BUS) is the sensitivity of CYGNSS SNR to spring melt onset. Spring melt onset refers to the beginning of melt of the overlying snow cover on the ice surface or of the ice surface in the absence of snow before BUS. Figure 3-7 displays a set of MODIS images showing an example of the evolution of the lake ice surface during the spring of 2022, where the melt onset starts on February 27 (as determined from MODIS albedo and ERA5-Land; see Figure 3-8). This process, which is associated with the temperature rise in springtime,

leads to the melt of on-ice snow and causes the lake ice surface to gradually become darker before the beginning of the breakup start (BUS) on March 16. In Figure 3-7, the images from the melt onset period are presented with red borders, whereas those from the breakup period are shown with blue borders.

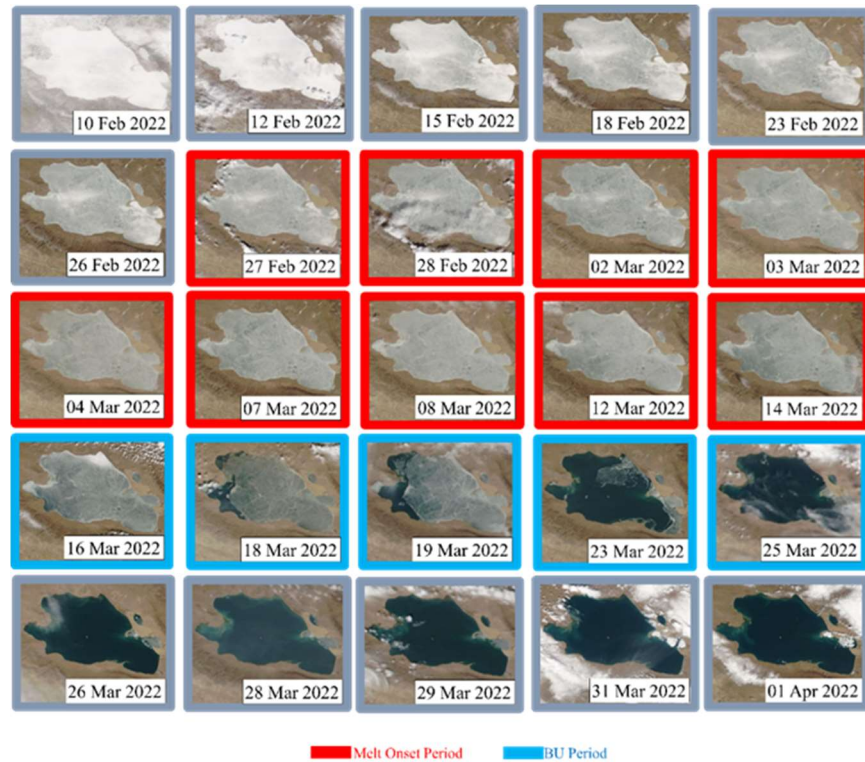


Figure 3-7. MODIS images for the springtime 2022. The images with red borders refer to the melt onset period before the breakup period, which is shown with images with blue borders. This figure shows how the lake ice surface becomes darker as the overlaying snow melts.

According to Howell et al. (2009), spring snow melt is associated with variations in lake ice surface conditions and results in a decrease in albedo. Figure 3-8 shows the changes in MODIS albedo values during the springtime for each year, in which the abrupt drops in albedo values suggest the initiation of melt onset before the BUS. These abrupt drops are associated with an increase in lake ice surface temperature. Figure 3-8 also includes breakup timing obtained from CYGNSS ($MTT > t_{0.001}$) and MODIS (visually determined). Comparing spring melt onset timing

with CYGNSS and MODIS breakup timing, one can see that CYGNSS timing clearly tends to be closer to the melt onset rather than BUS. This demonstrates the sensitivity of CYGNSS to the onset of spring melt before moving into the breakup period and open-water conditions.

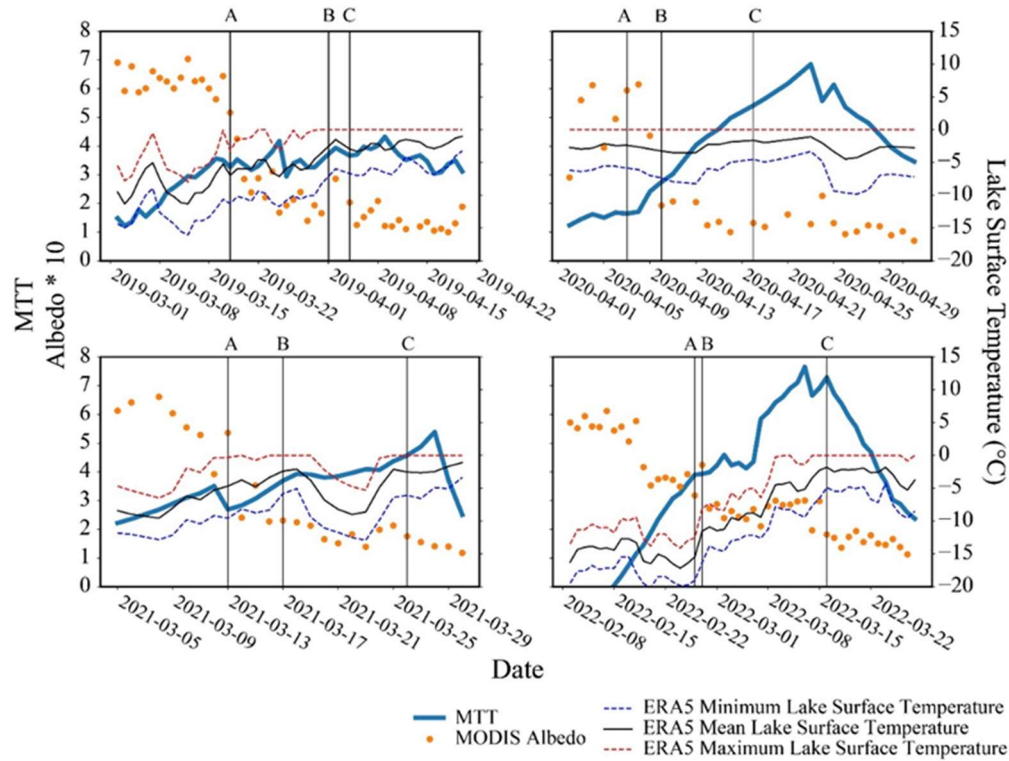


Figure 3-8. Surface albedo during springtime for each year along with MTT changes. Albedo values are scaled (multiplied by 10) for display on the same axis as MTT values. Dashed lines represent the maximum, mean, and minimum lake ice surface temperatures obtained from ERA5-Land data product. Vertical black lines correspond to estimated dates of melt onset (A) from MODIS surface albedo and ERA5-Land lake ice surface temperature, CYGNSS timing for BUS (B), and MODIS-derived timing for BUS (C). The vertical black lines clearly show the sensitivity of CYGNSS to the surface melt onset.

Based on timings determined from the MODIS albedo/ERA5-Land data products, CYGNSS SNR, and MODIS RGB images, which are presented together in Figure 3-8, Figure 3-9 provides a time frame for the spring of each year comparing each of those timings. The time difference between the initial melt and the CYGNSS-derived breakup ranges from 1 to 13 days with MBE and MAE of 4 and 5 days, respectively, while the difference between the start of actual

breakup as determined from MODIS and that of CYGNSS-derived breakup ranges from 3 to 18 days with MBE and MAE of -10 and 10 days, respectively.

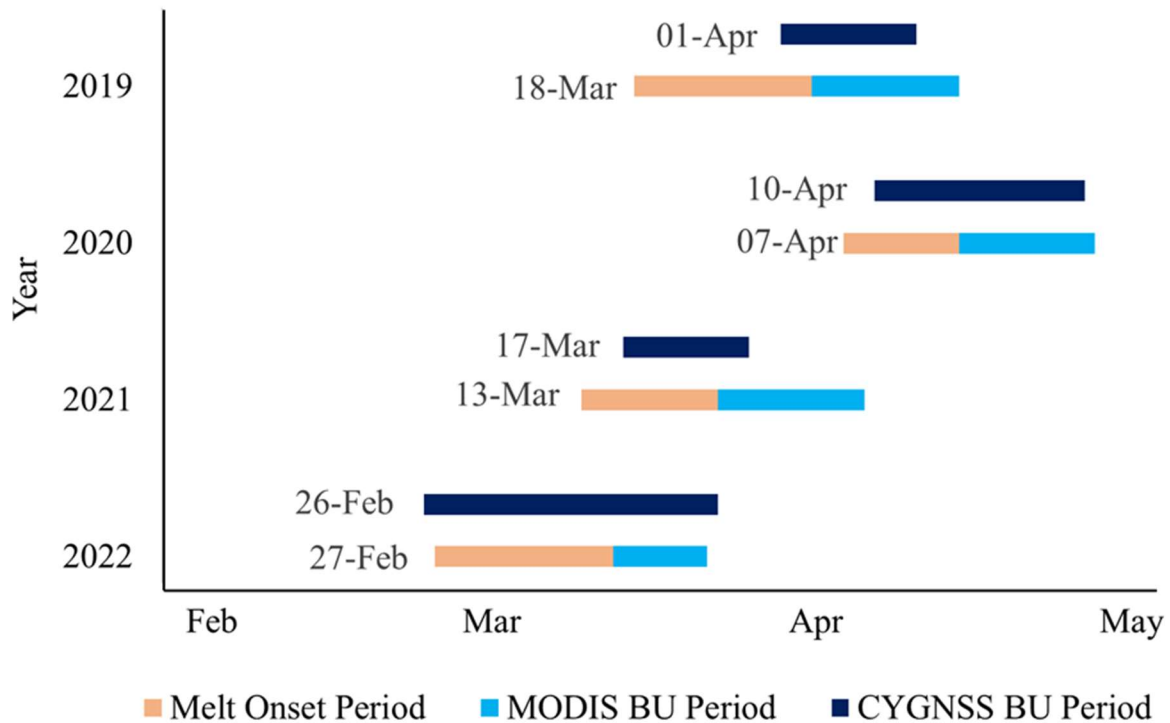


Figure 3-9. . CYGNSS BU period compared against the melt onset and BU periods obtained from MODIS. The BUS dates derived from CYGNSS are mostly closer to the melt onset dates rather than the BUS dates obtained from MODIS, which confirms the sensitivity of CYGNSS to the melt onset.

3.5.4. Qinghai Lake Ice Temporal Variability

Analysis of CYGNSS SNR, which includes four freeze-up and four breakup periods, suggests that Qinghai Lake starts freezing (FUS) on either the second or the third week of December, and the freezing process lasts (FUE) until the second week of January. The freeze-up period (FD) lasts 30 days on average. On the other hand, the BUS may occur between the third week of March and the third week of April, and the BUE ranges from the last week of March to

early May, suggesting that the average of BD is 13 days. These numbers are in close agreement with previous studies analyzing the temporal variability of Qinghai Lake ice cover. Using MODIS (surface reflectance) and Landsat (surface reflectance and TM/ETM+ images) products, Qi et al. (2019; 2020) characterized Qinghai Lake ice phenology between 2000 and 2016 and determined the FD and BD to be, on average, 25 and 13 days, respectively. The previous studies also analyzed the spatial variability of Qinghai Lake ice cover; however, the spatial pattern of FU and BU was not examined herein since daily averages of all observations recorded from the entire lake were considered for phenology analysis.

3.6. Conclusions

This study shows the ability of CYGNSS, as a space-based GNSS-Reflectometry platform, to assess the impact of lake surface (ice and open water) conditions on reflected GNSS signals and to determine the timing of lake ice phenology. Analysis of a four-year time series of CYGNSS-derived SNR values extracted over Qinghai Lake, we observed a strong agreement between abrupt changes in SNR and the timing of freeze-up and breakup events associated with lake ice phenology visually determined from MODIS RGB images. CYGNSS measured signals were shown to be sensitive to spring surface melt prior to the first appearance of open water (BUS). The analysis supports a general finding of a previous investigation by stating that the reflected GNSS signals from lake ice cover are significantly lower than those reflected from open water.

This investigation, however, was limited to only four years of observations over a single lake. To further assess the ability of GNSS-R to monitor lake ice phenology, follow-up studies are planned on lakes located at latitudes higher than Qinghai Lake, where GNSS-R systems can receive reflections. This will be possible with data acquired from recent and future spaceborne GNSS-R systems with polar orbits, e.g., HydroGNSS and Soil Moisture Active Passive

Reflectometry (SMAP-R) missions (Comite et al., 2020; Unwin et al., 2021; Asgarimehr et al., 2022). In addition, the analysis of data acquired along single tracks and within single footprints coincident with field measurement campaigns will further improve our understanding of the impact of lake ice conditions on reflected GNSS signals. Finally, other methods are to be explored to detect the coherency of reflections received from lakes to investigate changes in lake conditions. DDM waveform analysis using machine learning and deep learning techniques (e.g., Asgarimehr 2022) is among one of the topics we are examining to detect lake ice and determine the phenology timing of Tibetan Plateau lakes and lakes located at more northern latitudes.

Chapter 4 – Analysis of Fully Polarimetry GNSS-R Sensitivity to Lake Ice Cover Properties

Abstract - This paper presents the first analysis of full polarimetry Global Navigation Satellite System—reflectometry (GNSS-R) for the remote sensing of lake ice cover properties. Using data from the Soil Moisture Active Passive (SMAP) radar receiver acquired between October 2015 and December 2022, we evaluate the sensitivity of Stokes parameters (S_1 , S_2 , S_3), child Stokes parameters (ψ , χ , δ and m), and Normalized Bistatic Radar Cross Section (NBRCS; σ^0) to lake ice cover fraction and lake ice phenology. The study area for this investigation includes four large lakes located in Canada, namely Great Bear Lake (GBL), Great Slave Lake (GSL), Lake Athabasca, and Lake Winnipeg. Sensitivity analyses reveal correlations of up to 0.7 between the parameters of interest and lake-wide ice cover fraction. Furthermore, lake ice phenology analysis using SMAP-R parameters indicates the potential of full polarimetry GNSS-R for determination of the timing of ice phenology events, i.e., freeze-up start (FUS; the first appearance of ice on the lake), freeze-up end (FUE; once the lake becomes fully ice covered), break-up start (BUS; the appearance of the first pixel with open water over the lake ice), and break-up end (BUE; once the lake becomes ice-free), as well as surface melt onset (MO) prior to BUS. The uncertainty of full polarimetry GNSS-R derived lake ice phenology events is less than 5 days for most parameters analyzed. We further explore the use of regression models to enhance the accuracy of lake ice phenology timing estimation. By applying a Random Forest (RF) regression approach, we combined multiple polarimetric parameters to create a composite predictive model. The RF model identifies the σ^0 as the most significant feature during the ice formation period, demonstrating its importance in capturing lake ice freeze-up dynamics. However, during the BU period, Stokes parameters S_2 and S_3 became more significant indicating the variability in feature importance across different phenological events.

Keywords: Global Navigation Satellite System Reflectometry (GNSS-R), Hybrid Compact Polarimetry (HCP), Soil Moisture Active Passive (SMAP), Lake Ice

4.1. Introduction

Lakes occupy a significant fraction of the landscape in many regions of the northern hemisphere, with ice cover being present on them for several days, weeks or months of the year, depending on their location (Duguay et al., 2003). The importance of lake ice extends beyond the local scale, impacting regional weather, climate and ecosystems. The fractional coverage of ice on lakes (from ice-free to complete ice-cover conditions) has an impact on local and regional air temperature and precipitation (Rouse et al., 2005; Baijnath-Rodino et al., 2018; Eerola et al., 2014). The formation of lake ice is essential for the establishment of ice roads, which support economic activities and the transportation of goods (Murfitt and Duguay, 2021). Additionally, ice cover provides recreational opportunities, such as snowmobiling and ice fishing, which have substantial economic and social impacts (Cummings et al., 2019). Recognized as a sensitive indicator of climate change, lake ice cover (its extent, from which dates associated with ice phenology can be determined) has been designated as a thematic variable of Lakes as an essential climate variable (ECV) by the World Meteorological Organization's Global Climate Observation System (GCOS) (GCOS, 2022). Satellite remote sensing has become an essential tool for monitoring changes in lake ice cover in response to climate warming, and also to improve weather forecasts in lake-rich regions.

Recent investigations have assessed the utilization of signals acquired from satellite-based Global Navigation Satellite System Reflectometry (GNSS-R) sensors for the detection and monitoring of lake ice. Mayer and Ruf (2017) suggested the potential of Cyclone GNSS (CYGNSS) for altimetry purposes over lake ice. They proposed the idea of leveraging the

transparency of ice to GNSS L-band signals to estimate lake ice thickness. Later, Li et al. (2018) provided the initial evidence of the impact of freshwater ice on CYGNSS altimetry results over Qinghai Lake on the Tibetan Plateau during the winter of 2018, characterized by a reduction in water level during the ice season. Furthermore, Zavorotny et al. (2020) employed raw CYGNSS data from three specular tracks over Qinghai Lake to explore the scattering coherency of the lake during the open water and ice seasons. Their findings indicated greater signal-to-noise ratio (SNR) fluctuations in signals reflected from the ice compared to those from open water, attributed to the lower Fresnel reflection coefficient of the ice layer as opposed to the water surface. More recently, Ghiasi et al. (2023) have demonstrated the potential of CYGNSS for assessing the impact of lake surface conditions (ice and open water) on reflected GNSS signals and determining the timing of lake ice phenology events. The authors examined a four-year time series (August 2018 to August 2022) of SNR values obtained from CYGNSS over Qinghai Lake and observed a notable relation between abrupt changes in SNR determined by a moving t-test (MTT) algorithm and lake ice phenology events (i.e., dates associated with freeze-up and break-up) that were visually determined from the interpretation of MODIS color composite images.

In this research, we focus on the sensitivity of compact polarimetric GNSS-R to lake ice and open water conditions. Our analysis utilizes GNSS-R data from the Soil Moisture Active Passive (SMAP) mission's receiver. The SMAP radar captures L2 Global Positioning System (GPS) signals (frequency: 1227.6 MHz) reflected from the Earth's surface in both horizontal (H) and vertical (V) linear polarizations, functioning as a reflectometer or bistatic radar. This configuration, known as hybrid compact polarimetry (HCP) (Raney, 2021), is implemented for the SMAP reflectometer (SMAP-R) as the first satellite instrument of its kind. In the (Raney, 2021) investigation, the author states that the result of a circularly polarized transmissions is a balanced

illumination. Therefore, the resulting polarimetric portraits encompass all the polarimetric scattering information unique to the observed scene. This makes SMAP-R satisfy the original sense of fully polarimetric instrument. Consequently, the measurements enable computation of the full Stokes parameters. Notably, SMAP-R is not only the pioneer in full polarimetric GNSS-R but also the sole operational GNSS-R mission, offering the possibility of conducting extensive analyses of the northern cryosphere, with a data record exceeding seven years. The polarization setup allows for the computation of the Stokes and child Stokes parameters, whose detailed mathematical description and calibration methodology are provided in Rodriguez-Alvarez et al. (2024) and Munoz-Martin et al. (2022) . For this article, SMAP-R data are used to examine the overall variability of the Stokes and child Stokes signals from 2015 to 2022 across four distinct Canadian lakes along a latitudinal gradient: Great Bear Lake, Great Slave Lake, Lake Athabasca, and Lake Winnipeg. Here, we introduce polarimetric GNSS-R signatures observed in the SMAP-R dataset in the form of full polarimetric GNSS-R for the assessment of the impact of lake ice from initial formation through to complete open water conditions on reflected GNSS signals. Previous studies have demonstrated the potential of SMAP-R polarimetric GNSS-R information for cryosphere monitoring, including Arctic sea ice, freeze/thaw dynamics of the ground in northern latitudes, and the Greenland ice sheet (Rodriguez-Alvarez et al., 2023). This paper is the first to evaluate the use of SMAP-R data for lake ice through a bistatic radar configuration, specifically a polarimetric representation of GPS forward scattering. Alongside the Stokes and child Stokes parameters, we also analyze the Normalized Bistatic Radar Cross Section (NBRCS), which is computed as an observable for non-polarimetric missions, such as CYGNSS, as well.

4.2. Study Areas

The research area encompasses four Canadian lakes: Great Bear Lake (GBL), Great Slave Lake (GSL), Lake Athabasca, and Lake Winnipeg (Figure 4-1). The four lakes become fully ice-covered during the winter but display different timings regarding ice formation and decay and the length of the ice season due to their geographical setting along a north-to-south latitudinal gradient.

GBL (66° N, 121° W) is located in the Northwest Territories and has a surface area of 31,000 km² and a mean depth of 76 m, with a maximum depth of 446 m. The lake discharges into the Mackenzie River via the Great Bear River. Positioned within the high-latitude continental Mackenzie River Basin (MRB), GBL experiences monthly near-surface air temperatures ranging from -25°C to -35°C in winter and 15°C to 20°C in summer. GBL is fully ice-covered on average from mid-December to mid-June.

GSL ($61^{\circ}40'$ N, 114° W), also situated in the Northwest Territories, has a surface area of 29,000 km², a mean depth of 41 m, and a maximum depth of 614 m. The lake receives inflow from various rivers, including the Hay and Slave Rivers. Like GBL, the region where the lake is located experiences significant air temperature variations, with monthly temperatures ranging from -25°C to -35°C in winter and 15°C to 20°C in summer. GSL is fully ice-covered, on average, between mid-December and mid-May.

Lake Athabasca (59° N, 109° W), the largest and deepest lake in both Alberta and Saskatchewan, has a surface area of 8,000 km² and a mean depth of 26 m, with a maximum depth of 124 m. The lake receives inflow from the Athabasca and Peace Rivers and flows northward into GSL through the Slave River and Mackenzie River systems, eventually reaching the Arctic Ocean. Mean monthly air temperatures range from -25°C to -10°C in winter and 10°C to 15°C in summer. The lake is usually fully ice-covered from mid-December to mid-May.

Located in Manitoba, Lake Winnipeg (50° N, 97° W) has a surface area of 24,000 km², a mean depth of 12 m, and a maximum depth of 36 m. The lake is fed by several rivers, including the Saskatchewan, Red, and Winnipeg Rivers, and its main outflow is the Nelson River. Mean monthly air temperatures range from -20°C to -5°C in winter and 10°C to 20°C in summer. Lake Winnipeg is fully ice-covered from mid-December to early May.

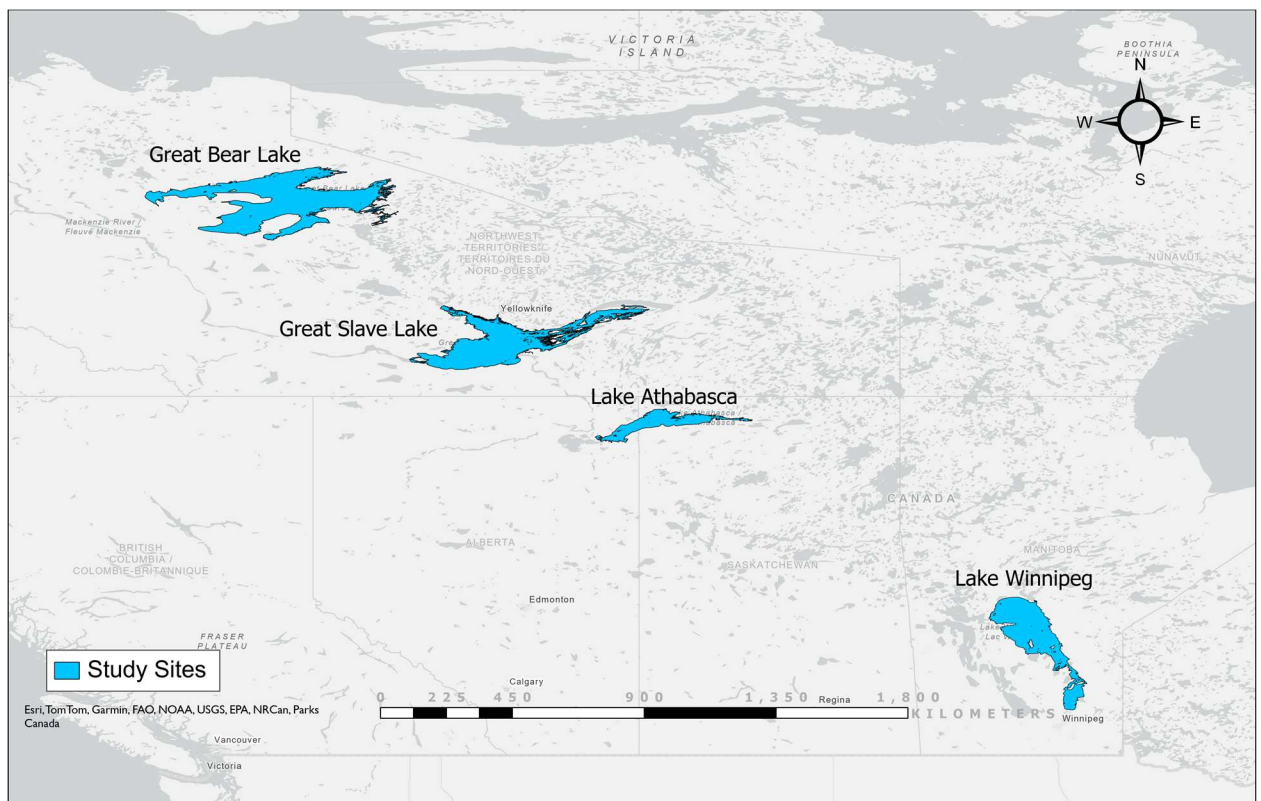


Figure 4-1. Location of the study areas; four Canadian Lakes, GBL, GSL, Lake Athabasca, and Lake Winnipeg

4.3. Data and Methods

4.3.1. SMAP-R Data

The Soil Moisture Active Passive (SMAP) mission was launched on January 31, 2015, with its primary goal being to provide global soil moisture and freeze/thaw state measurements

every 2-3 days (Piepmeier et al., 2017). SMAP is equipped with two instruments: a radiometer and a radar; however, on July 7, 2015, the radar experienced a malfunction. On August 20, 2015, the SMAP radar receiver's center frequency was adjusted to 1227.6 MHz, allowing it to receive GPS L2 signals reflected off the Earth's surface. This development marked SMAP's transition into one of the most recent GNSS-R missions known as SMAP-R. The average spatial resolution of SMAP-R footprints over the lakes of interest is 24 km.

The GPS satellite constellation transmits signals with right-hand circular polarization (RHCP). SMAP-R, on the other hand, captures both the horizontal (H) and vertical (V) components of the RHCP signal reflected off the Earth's surface. Consequently, the data collected by SMAP-R comprises RH and RV components. This specific configuration, involving RH and RV components for SMAP-R, is referred to in existing literature as a hybrid compact polarimetry bistatic radar (Munoz-Martin et al 2023), but in the case of GNSS-R the resulting polarimetric portraits encompass all the polarimetric scattering information unique to the observed scene and therefore satisfy the original sense of fully polarimetric instrument as described in (Raney, 2021). Then, the polarimetric components are converted to four Stokes parameters. The data obtained from SMAP-R, as with any GNSS-R receiver, consists of delay-Doppler maps (DDMs) depicting the power distribution of GPS signals across the Earth's surface at various delay and Doppler values (Zavorotny and Voronovich, 2000). In SMAP-R, the four Stokes parameters correspond to four distinct DDMs, which are defined as follows:

$$\begin{aligned}
S_0 &= \langle |E_{RH}|^2 \rangle + \langle |E_{RV}|^2 \rangle \\
S_1 &= \langle |E_{RH}|^2 \rangle - \langle |E_{RV}|^2 \rangle \\
S_2 &= 2 \operatorname{Re} \langle \{E_{RH} E_{RV}^*\} \rangle
\end{aligned} \tag{4.1}$$

$$S_3 = 2 \text{Im}\langle\{E_{RH}E_{RV}^*\}\rangle$$

where E_{RH} and E_{RV} are the complex electrical field received by the H and V SMAP antennas, respectively, after the correlation with the GPS pseudo-random noise (PRN) sequence. Here, $\langle \rangle$ is an average operation over time. The last three Stokes parameters (S_1 , S_2 , and S_3) can be normalized to S_0 , which is the total intensity received at the H and V antennas. In this study, normalized Stokes parameters are used. Stokes parameters and their normalized values along with calibrated normalized bistatic radar cross section (σ^0) for each specular point has been calculated and provided in SMAP-R metadata. The full mathematical procedures and calibrations can be found in (Rodriguez-Alvarez et al., 2022; Munoz-Martin et al., 2022).

In addition to Stokes parameters, the child Stokes parameters have shown potential in cryosphere monitoring (Rodriguez-Alvarez et al., 2023b; 2024). The child Stokes parameters can be derived from the Stokes parameters as follows:

$$\begin{aligned}\psi &= 0.5 \arctan(S_2/S_1) \\ \chi &= 0.5 \arctan(S_3/\sqrt{S_1^2 + S_2^2}) \\ \delta &= \arctan(S_3/S_2) \\ m &= \left(\sqrt{S_1^2 + S_2^2 + S_3^2}\right)/S_0\end{aligned}\tag{4.2}$$

where ψ is the polarization angle, χ is the ellipticity of the received wave, δ is the phase difference between E_{RH} and E_{RV} , and m is the degree of polarization.

This study used Stokes and child Stokes parameters, as well as reflectivity, obtained from the four lakes of interest from 1 October 2015 to 31 December 2022. Table 4-1 provides a summary

of SMAP-R data used in this study for each lake. Figure 4-2 shows all SMAP-R specular tracks recorded over each lake of interest from 1 October 2015 to 31 December 2022.

Table 4-1. SMAP-R data description summary for each lake of interest

Lake	No. of Total Tracks	No. of Total SP	Average Revisit Time	Average No. of SP on each Track
GBL	559	2029	1.4 days	3.6
GSL	321	1145	2.5 days	3.5
Athabasca	202	266	11 days	1.31
Winnipeg	159	665	4.4 days	4.18

Figure 4-2 shows all SMAP-R specular tracks recorded from 1 October 2015 to 31 December 2022 over each lake of interest.

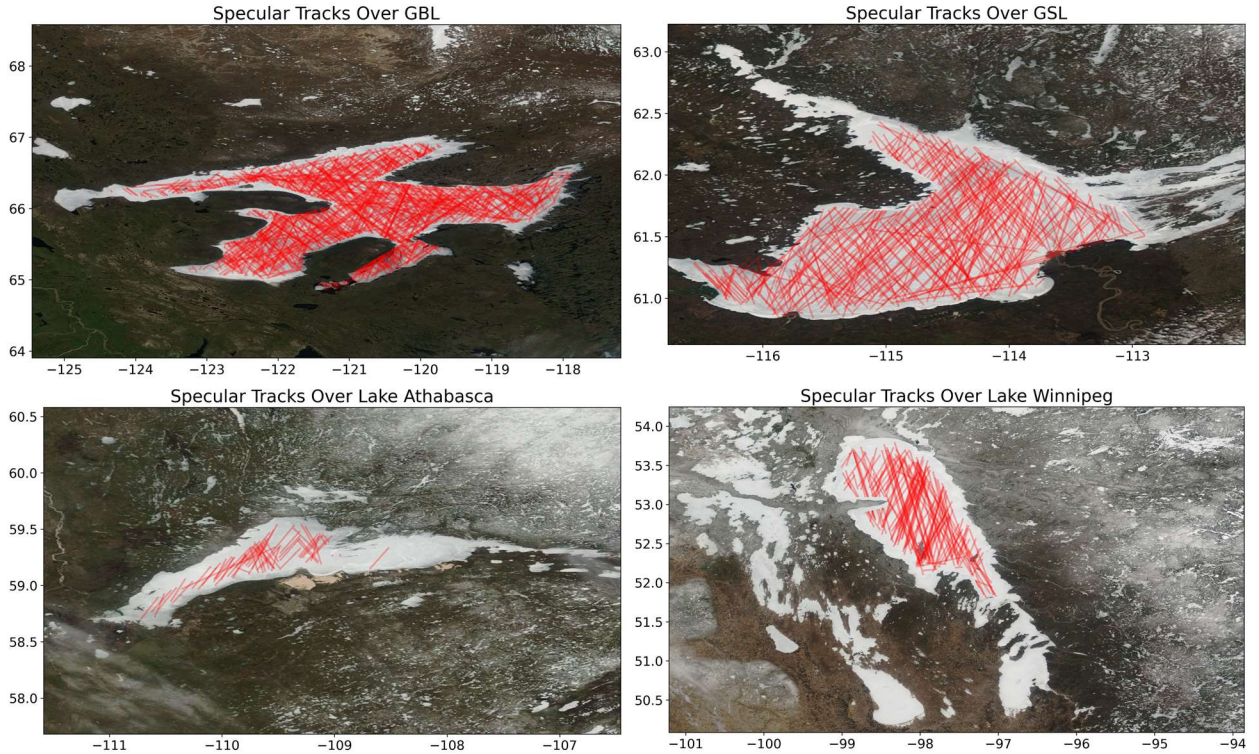


Figure 4-2. SMAP-R specular tracks over each lake of interest, i.e., GBL, GSL, Lake Athabasca, and Lake Winnipeg, during the study period, i.e., from 1 October 2015 to 31 December 2022.

4.3.2. Auxiliary Data

Moderate Resolution Imaging Spectroradiometer (MODIS) true color composite (composed of Red from band 1, Green from band 4, and Blue from band 3 (RGB); Gumley et al., 2003) images were employed to visually ascertain the dates corresponding to the freeze-up and breakup periods of the lakes of interest. From the MODIS RGB images, the freeze-up period was identified as the interval starting from the first date when the ice cover became visible (freeze-up start = FUS) until the first date when the ice entirely covered the lake surface (freeze-up end = FUE). The breakup period, on the other hand, spanned the time between the date of the initial appearance of water (break-up start = BUS) and the complete disappearance of the ice cover from the lake (break-up end = BUE). However, the precision of the dates determined from visual interpretation of MODIS images is influenced by the presence of cloud cover and solar

illumination conditions, introducing some uncertainty in the determination of phenology dates. For instance, FUE timing for GBL through MODIS images is not possible since it happens in the polar night; therefore, other data sources were also used to determine lake ice phenology dates.

A secondary lake ice product was obtained from the Canadian Ice Service (CIS). The product contains values representing the ice fraction in tenths (ranging from 0 for open water to 10 for complete ice cover) for approximately 140 lakes in Canada and the northern United States. This estimation is based on the visual interpretation of imagery from Advanced Very High Resolution Radiometer (AVHRR) provided by the National Oceanic and Atmospheric Administration (NOAA) at a 1.1 km resolution, RADARSAT ScanSAR at a 100 m resolution, as well as MODIS (250–500 m) and Visible/Infrared Imaging Radiometer Suite (VIIRS) I-band (375 m) observations by ice analysts. The CIS product furnishes a single, lake-wide value for each lake on a weekly basis. Due to the weekly nature of the product, the specific occurrence dates of the determined ice fractions may exhibit variations of up to seven days. Using the ice fractions provided by CIS, we define BUS as the first week in which the fraction transitions from 10 tenths to below 10 tenths, and BUE as the first week in which the fraction reaches 0 tenth. During freeze-up, FUS is marked by the initial week in which the fraction transitions from 0 tenth to 1 tenth, and FUE is defined as the first week in which the fraction reaches 10 tenths. It should be noted that CIS records weekly ice fractions for two sections for each of GBL (north and south), GSL (northwest and southeast), and Lake Winnipeg (north and south). In this study, fractions are averaged and compared against patterns achieved from SMAP-R for each lake.

Another ice product used is the daily snow and ice product from the NOAA Interactive Multisensor Snow and Ice Mapping System (IMS; U.S. National Ice Center 2008). This cloud-free product contains data on the extent of snow and ice cover on a 1 km grid, which was introduced

in December 2014. The product is generated from a combination of ground observations, when available, and a wide range of satellite data sources, including AVHRR, Geostationary Operational Environmental Satellite (GOES), Special Sensor Microwave/Imager (SSM/I), and Advanced Microwave Sounding Unit (AMSU), as described in Helfrich et al. (2007). Previous research has demonstrated that IMS data is a valuable tool for conducting studies related to lake ice phenology (e.g., Brown and Duguay, 2012, 2013; Kang et al., 2012). In this study, the IMS dataset was used to determine the presence of open water or ice cover in each pixel over each lake of interest. Using IMS, the first date on which a first ice pixel appears ice-covered is defined as FUS and the date on which all pixels over the lake surface are marked as ice for the first time is referred to as FUE. Similarly, BUS corresponds to the date on which the first water pixel appears over the lake, while BUE is defined as the full disappearance of ice pixels from the lake surface.

The detection of the beginning of snow/ice surface melt before the first appearance of open water can be performed by employing MODIS daily albedo products from the Terra and Aqua satellites (MOD/MYD10A1, daily, level 3, version 6). The products are specifically generated for dates with clear skies and snow-covered surfaces, representing the reflectance anisotropy of MODIS pixels at a spatial resolution of 500 m (Wang et al., 2012). These data have previously been employed for studying the decreasing albedo of lake ice during breakup (Svacina et al., 2014). Here, the daily average albedo for the entire lake was computed, enabling the identification of spring melt onset (MO) characterized by a continuous decline in albedo until the emergence of open water, i.e., BUS. Due to the intermittent occurrence of clear-sky conditions, the surface albedo values were cross-referenced with MODIS images, revealing an average uncertainty of one day during MO across each of the four lakes. This decrease during spring melt is strongly controlled by the lake surface temperature, i.e., melting vs subfreezing (Duguay et al., 2003);

therefore, we also utilized hourly data from the ERA5-Land reanalysis obtained from the European Centre for Medium-Range Weather Forecasts (ECMWF) to be used, along with the MODIS albedo products, to determine melt onset dates for each lake. The ERA5-Land product includes 2-m air temperature with a spatial resolution of 9 km (Muñoz-Sabater, 2021).

4.3.3. SMAP-R Analysis Over Lake Ice

This study has two main goals: 1) Analyze the impact of lake surface conditions on full polarimetry GNSS-R signals, and 2) evaluate the potential of full polarimetry GNSS-R observables for the determination of lake ice phenology timing.

Firstly, we evaluate the sensitivity of the full-polarimetry GNSS-R signals to lake surface conditions. For this purpose, we evaluate the general pattern of Stokes and child Stokes parameters along with σ^0 under different surface conditions for each lake during the open water, FU, ice growth season, and BU periods. Next, we compare each of the parameters of interest against auxiliary data to quantify the relationship between these parameters and lake surface indices, i.e., lake ice fraction obtained from CIS and the frozen state of areas associated with each SMAP-R footprint acquired from the IMS dataset. To use CIS-derived data, we assumed each lake as one object; therefore, to make full polarimetry GNSS-R observables compatible with the CIS dataset, we averaged all SMAP-R observations on a weekly basis. On the other hand, IMS provides pixel-wise data for the lake surface state (frozen/open water) on a daily basis. Hence, each SMAP-R specular point was compared with a co-located 5x5 km grid cell from the IMS dataset. A grid cell was classified as frozen if more than 50% of its area was labeled as lake ice in the IMS dataset; otherwise, it was classified as open water.

Secondly, we assess the potential of full polarimetry GNSS-R in lake ice phenology analysis by evaluating abrupt changes in SMAP-R parameters time series. To this aim, for each parameter of interest, we plotted all observations together in one-year graphs along with the average phenology dates, i.e., FUS, FUE, BUS, BUE, to see the sensitivity of each observable to the lake ice phenology events. Then, a moving t-test (MTT) analysis, as explained in Ghiasi et al. (2023), was conducted for each parameter of interest to detect abrupt changes and compare them with the average phenology dates of each lake. For each time series, we consider a period as an abrupt change period in which the MTT values are greater/smaller than the average $\pm$ standard deviation. Moreover, MO dates were calculated based on MOIDS albedo data products to investigate the sensitivity of full polarimetry GNSS-R parameters to the spring MO.

4.4. Results and Discussion

4.4.1. SMAP-R Analysis for Lake Ice Surface Condition

To evaluate the sensitivity of each parameter, we compare each of the SMAP-R parameters with two auxiliary datasets, i.e., CIS and IMS, which provide information on lake ice fraction and pixel-wise freezing state, respectively, over each lake of interest. Figure 4-3 displays a correlation matrix that uses color- and scale-coding to quantify the correlation between lake ice fractions obtained from CIS for each lake and each of the SMAP-R parameters. The correlations are calculated for BU periods only (Figure 4-3, top row), and FU periods only (Figure 4-3, bottom row), separately.

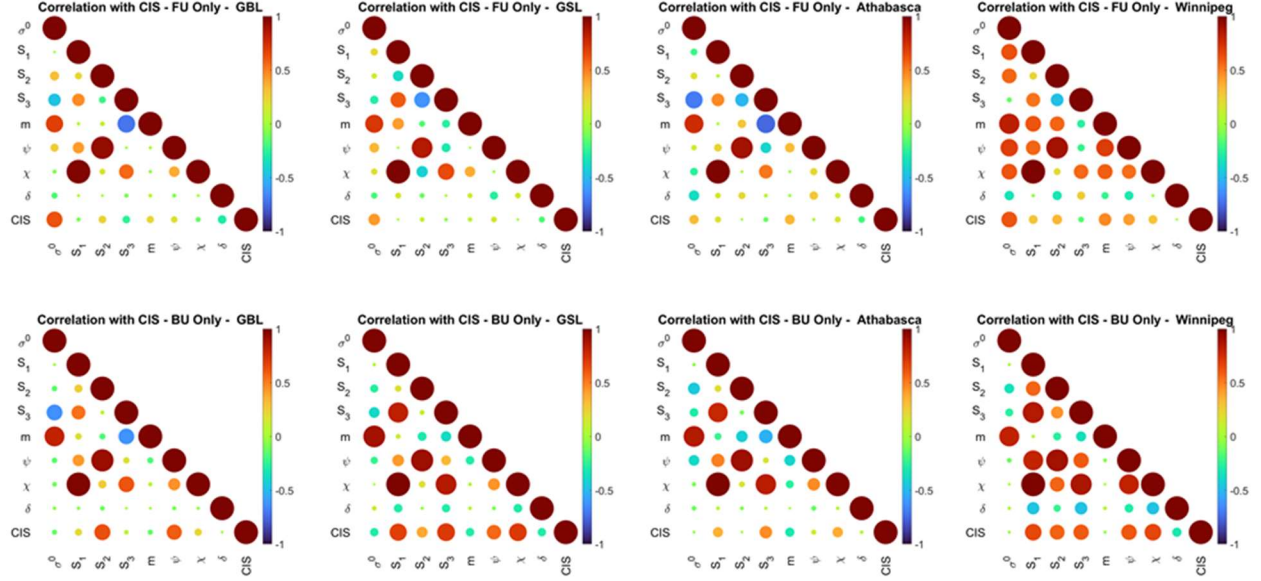


Figure 4-3. Correlation matrix between lake ice fraction obtained from CIS and each of the SMAP-R parameters of interest over two periods of FU (top) and BU (bottom)

During the FU periods, the lake ice fractions over all four lakes, i.e., GBL, GSL, Lake Athabasca, and Lake Winnipeg, have the highest correlation with σ^0 , which are 0.63 ($p < 0.001$), 0.43 ($p < 0.01$), 0.33 ($p < 0.1$), and 0.62 ($p = 0.02$), respectively.

On the other hand, the correlation matrices have different patterns during BU periods, in which the lake ice fraction over each lake shows the highest correlation with different SMAP-R parameters. CIS-obtained lake ice fraction for GBL during BU periods has the highest correlation with S_2 (0.63) followed by ψ (0.60) both with p-values < 0.001 . GSL lake ice fractions show the highest correlation with χ and S_3 (both 0.72) followed by S_1 (0.69) all with p-values < 0.001 . The correlation matrix for Lake Athabasca gives similar information to GSL, in which those three parameters, i.e., S_3 , χ , and S_1 , have the higher correlations with lake ice fraction, which are 0.47 ($p < 0.05$), 0.37 ($p < 0.1$), and 0.36 ($p < 0.1$). Finally, Lake Winnipeg ice fractions during the BU periods have a correlation of 0.67 with S_1 and χ , with the lake ice fractions both with p-values < 0.001 .

Moreover, full polarimetry GNSS-R analysis for lake surface condition during the BU periods reveals that the behaviors of the first two Stokes parameters, i.e., S_1 and S_2 , tend to alternate in different study areas. It can be seen that for GBL, S_2 shows the highest correlation with lake ice fractions obtained from the CIS dataset, while for GSL and Lake Winnipeg, S_1 is among the parameters with very high correlations with lake ice fractions. This phenomenon can be attributed to the sensitivity of S_1 and S_2 to the linear polarization response of the signal. Previous research has shown that these parameters can shift relative to one another due to polarization rotation induced by the ionosphere, a factor that has been accounted for in the calibration of SMAP-R data (Munoz-Martin et al., 2023). However, the variations observed in this study likely stem from different factors, such as the changing surface conditions of the lakes—ranging from open water to lake ice—or potential signal interference from adjacent landmasses in certain lakes compared to others.

In addition to CIS data, we used IMS data to evaluate how the frozen state of a single footprint may modify the SMAP-R observables. To this aim, we acquired the freezing state of each SMAP-R footprint from the IMS dataset during the FU and BU periods separately and then calculated and compared the average and STD of each parameter over frozen lake and open water of each year for each lake of interest. Figures 4-4 and 4-5 represent the average value of each SMAP-R parameter for each year over lake ice and open water for our four lakes of interest during FU and BU periods. The size of markers in each graph represents the STD of that parameter; the larger a marker is, the greater the associated STD value is. No specific pattern is observed from the IMS dataset shown in Figures 4-4 and 4-5, confirming that SMAP-R observables are less sensitive to the frozen state of single footprints encompassing only a few pixels.

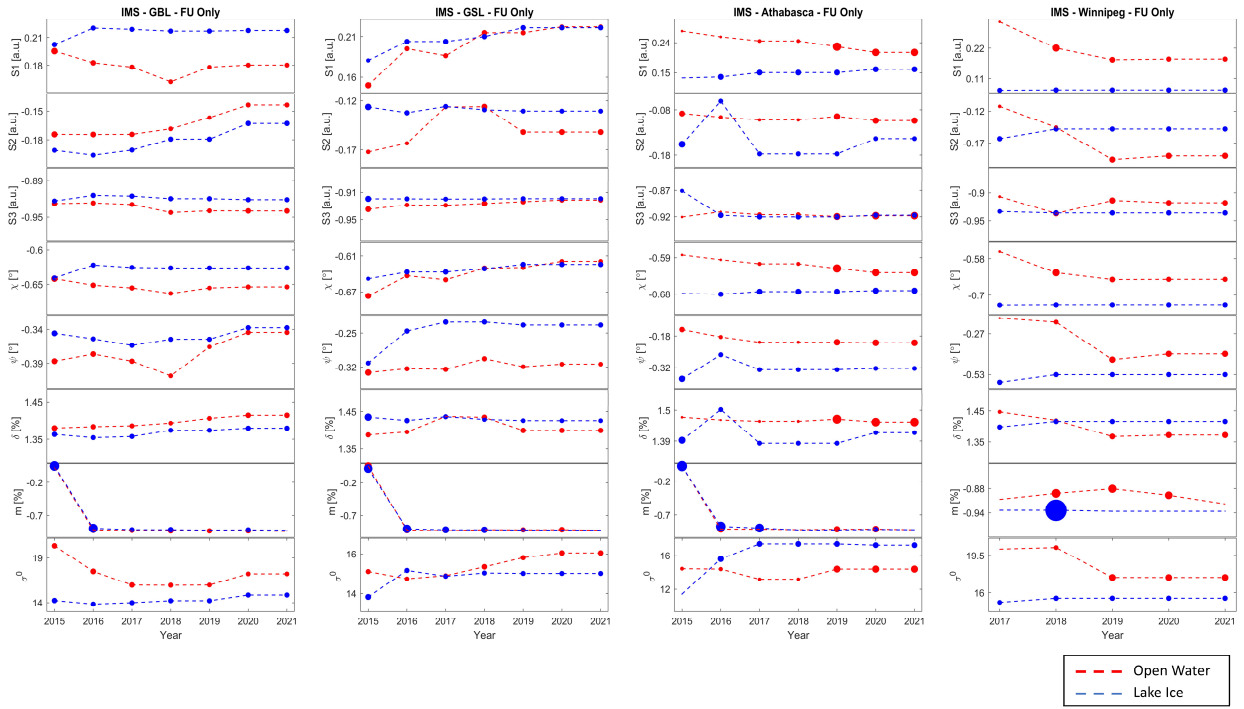


Figure 4-4. The average of each SMAP-R parameter of interest over frozen (blue) and open water (red) regions obtained from IMS data over the FU periods. The size of markers is associated to the standard deviation.

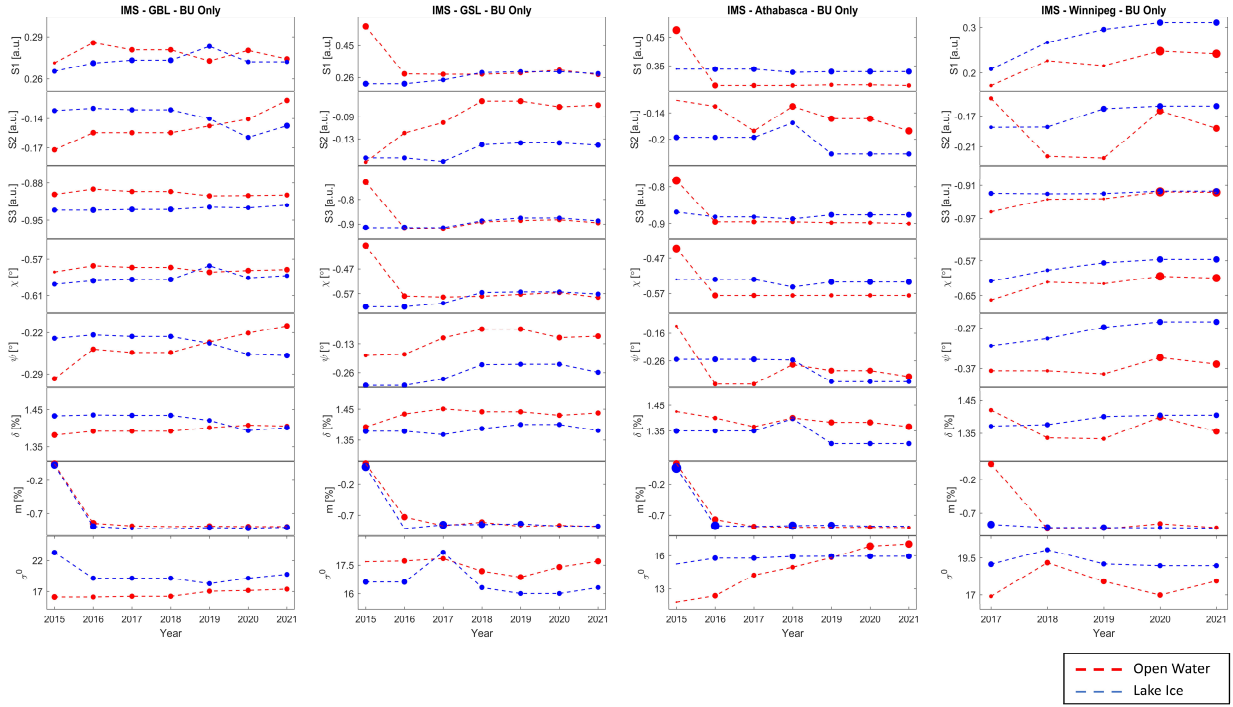


Figure 4-5. The average of each SMAP-R parameter of interest over frozen (blue) and open water (red) regions obtained from IMS data over the BU periods. The size of markers is associated to the standard deviation.

Comparing the results obtained with the CIS (Figure 4-3) and IMS (Figures 4-4 and 4-5) datasets, it can be concluded that the full polarimetry GNSS-R parameters are more sensitive to the lake-wide ice fraction rather than the frozen state of the lake surface associated with SMAP-R footprints. This can be explained through the sensitivity of full polarimetry GNSS-R parameters to lake surface roughness. The CIS dataset considers each lake as a single object, reflecting the roughness information more effectively. In contrast, the IMS dataset provides information for each pixel individually, lacking roughness information. Consequently, this explains why the CIS dataset has a significant correlation with some of the polarimetric parameters of full polarimetry GNSS-R, compared to the IMS datasets.

4.4.2. SMAP-R Potential for Lake Ice Phenology Timing

As discussed in Section 4.4.1. and shown in Figure 4-3, we observed the sensitivity of the polarimetric parameters of full polarimetry GNSS-R to lake ice surface conditions and ice presence. Therefore, in this section, we aim to evaluate its potential for lake ice phenology timing. We first plotted each of the SMAP-R data, i.e., normalized Stokes parameters, child Stokes parameters, and σ^0 , for the lakes of interest for each year. Figures 4-6 to 4-9 show the SMAP-R parameters variation for GBL, GSL, Lake Athabasca, and Lake Winnipeg, respectively, over the period of August 2016 to August 2017, as an example. In these figures, lake ice phenology dates, i.e., BUS, BUE, FUS, and FUE, obtained from CIS dataset are presented as vertical lines. Furthermore, daily maximum, average, and minimum 2-meter air temperature obtained from ERA5-Land are shown in red lines.

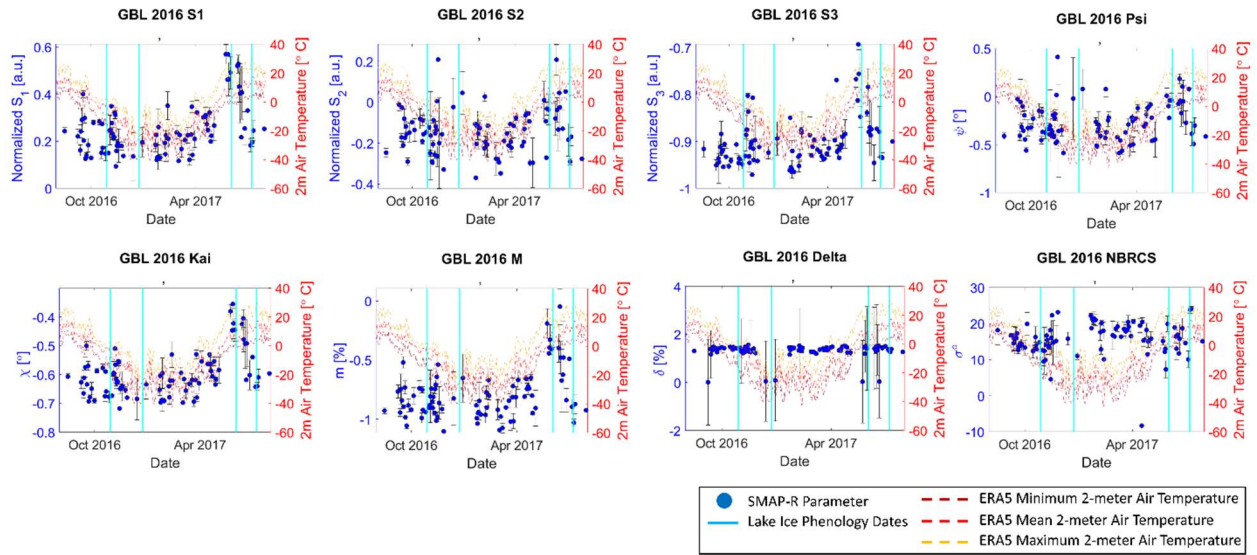


Figure 4-6. SMAP-R data (blue dots) and their STD (black lines) for GBL from August 2016 to August 2017. Blue vertical lines represent phenology dates, i.e., BUS, BUE, FUS, and FUE, respectively from left to right. Dashed lines represent minimum, average and maximum 2-meter air temperature.

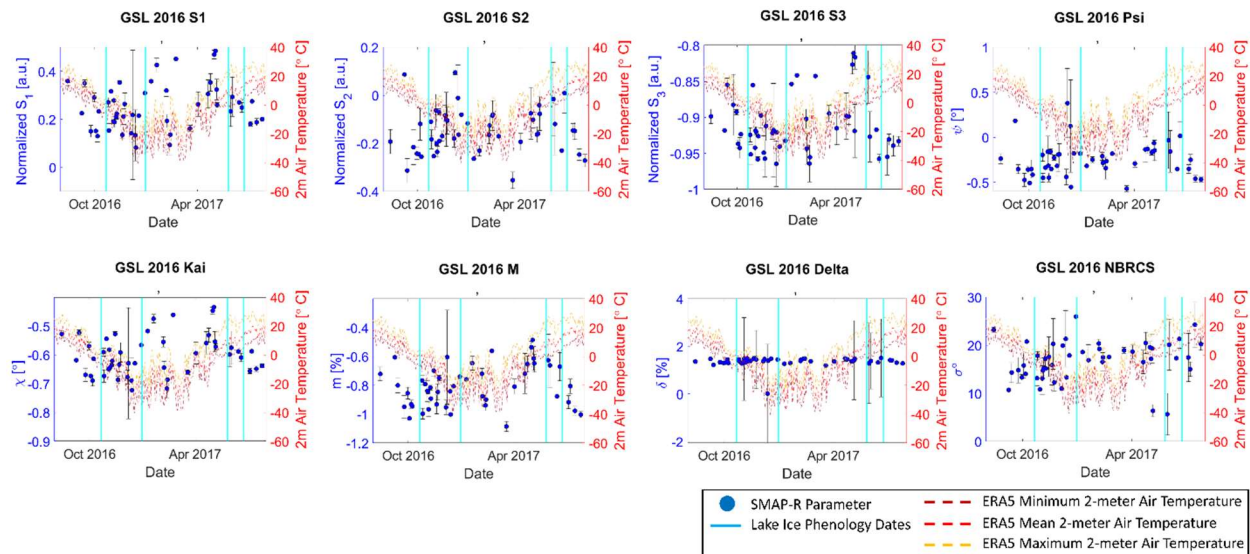


Figure 4-7. SMAP-R data (blue dots) and their STD (black lines) for GSL from August 2016 to August 2017. Blue vertical lines represent phenology dates, i.e., BUS, BUE, FUS, and FUE, respectively from left to right. Dashed lines represent minimum, average and maximum 2-meter air temperature.

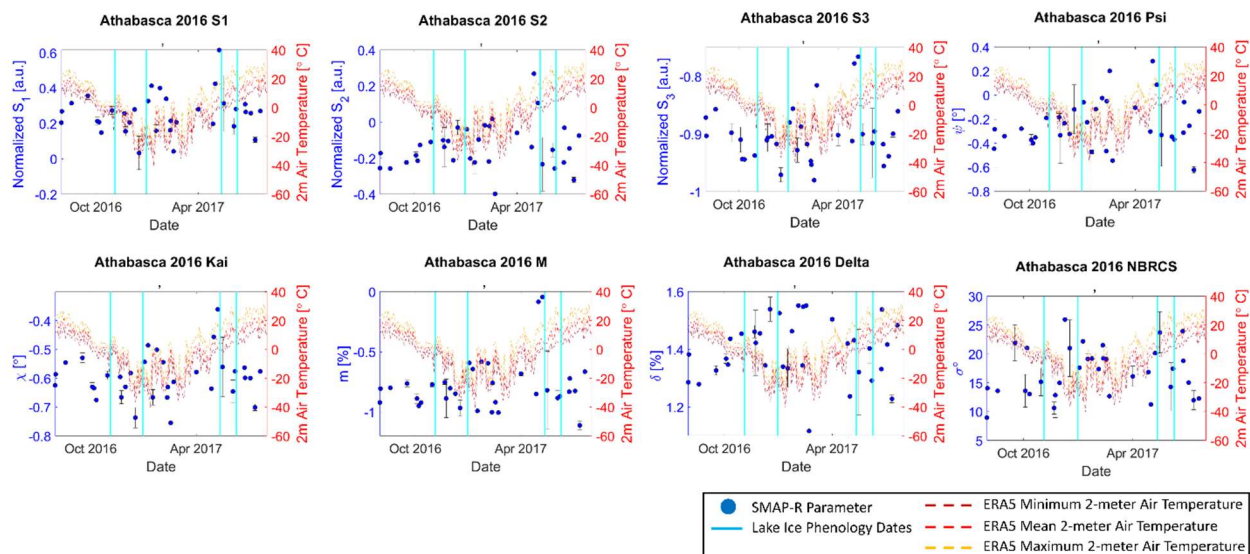


Figure 4-8. SMAP-R data (blue dots) and their STD (black lines) for Lake Athabasca from August 2016 to August 2017. Blue vertical lines represent phenology dates, i.e., BUS, BUE, FUS, and FUE, respectively from left to right. Dashed lines represent minimum, average and maximum 2-meter air temperature.

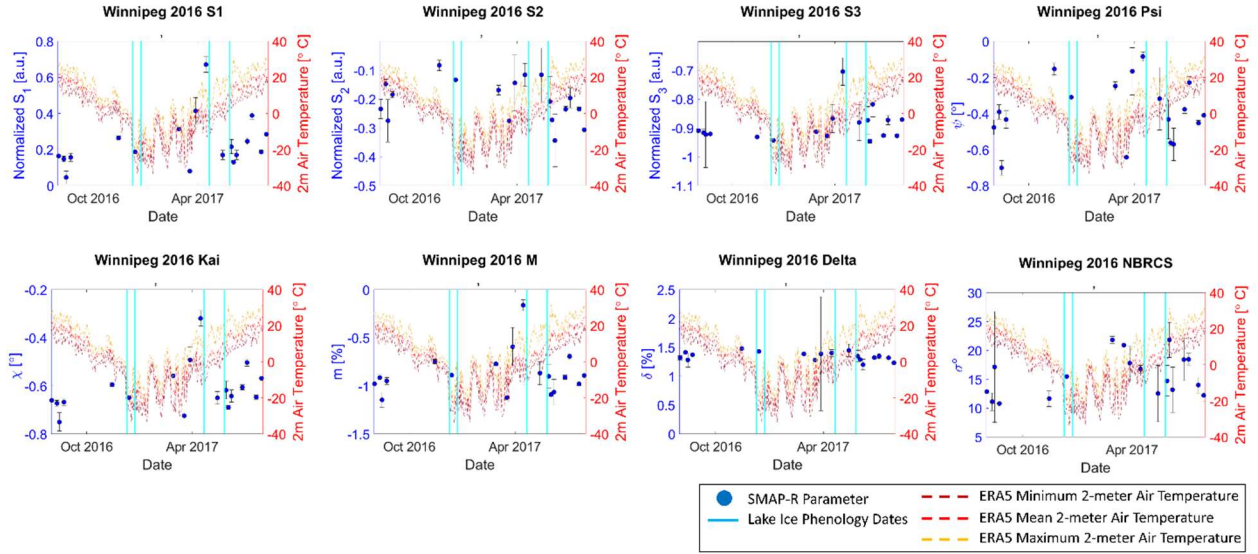


Figure 4-9. SMAP-R data (blue dots) and their STD (black lines) for Lake Winnipeg from August 2016 to August 2017. Blue vertical lines represent phenology dates, i.e., BUS, BUE, FUS, and FUE, respectively from left to right. Dashed lines represent minimum, average and maximum 2-meter air temperature.

To better illustrate the variation of SMAP-R data and evaluate the potential for lake ice phenology assessment, data from all years are then plotted together along with the average of lake ice phenology dates for each lake. The averaging process for lake ice phenology dates was weighted based on the number of specular points in each year. the average of MO dates is also added to evaluate the sensitivity of full polarimetry polarimetric parameters to the spring melt prior to the actual breakup. Figures 4-10 to 4-13 represent the combination of all yearly observations for each lake and for each SMAP-R parameter. In addition, an MTT analysis, as well as dates associated with MTT abrupt changes, are added to each figure. In addition, Table 4-2 contains information on the MTT abrupt changes for each SMAP-R parameter for each lake during FU and BU periods, along with the average phenology dates.

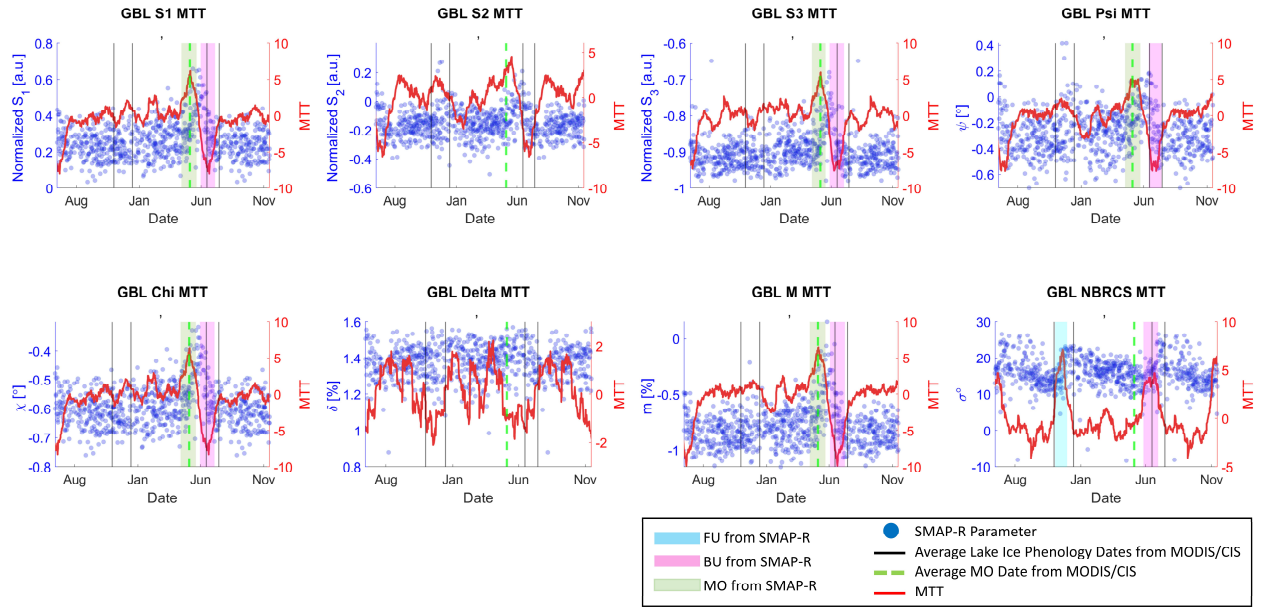


Figure 4-10. Daily SMAP-R data (blue dots) for GBL from October 2015 to December 2022. Black vertical lines represent the average of phenology dates, i.e., BUS, BUE, FUS, and FUE, respectively from left to right. Green dashed lines are the MO time. Phenology and MO lines are obtained from reference sources, i.e., MODIS and ICS. Red lines represent MTT values. Blue, pink, and green bars are FU, BU, and MO periods, respectively, obtained from MTT abrupt changes for each parameter.

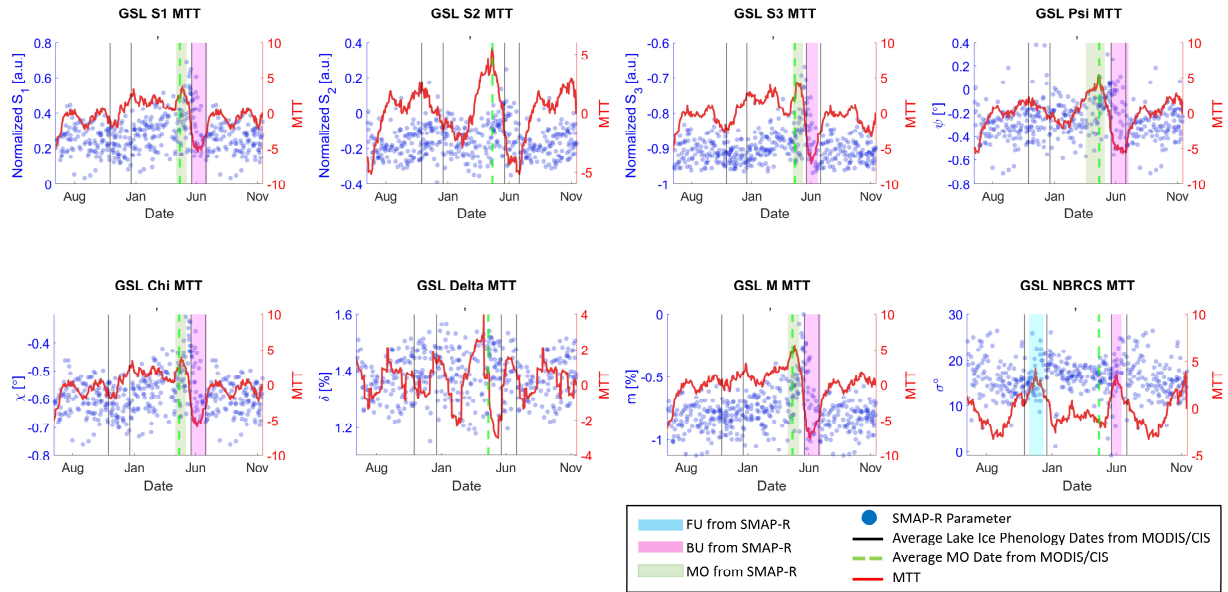


Figure 4-11. Daily SMAP-R data (blue dots) for GSL from October 2015 to December 2022. Black vertical lines represent the average of phenology dates, i.e., BUS, BUE, FUS, and FUE, respectively from left to right. Green dashed lines are the MO time. Phenology and MO lines are obtained from reference sources, i.e., MODIS and ICS. Red lines represent MTT values. Blue, pink, and green bars are FU, BU, and MO periods, respectively, obtained from MTT abrupt changes for each parameter.

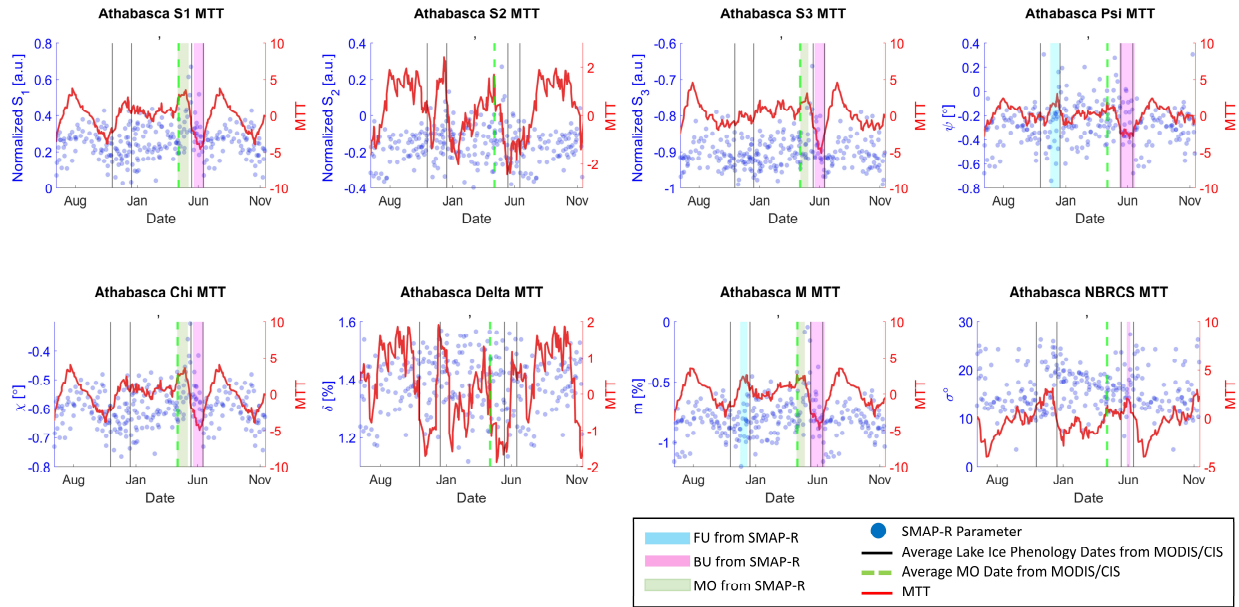


Figure 4-12. Daily SMAP-R data (blue dots) for Lake Athabasca from October 2015 to December 2022. Black vertical lines represent the average of phenology dates, i.e., BUS, BUE, FUS, and FUE, respectively from left to right. Green dashed lines are the MO time. Phenology and MO lines are obtained from reference sources, i.e., MODIS and ICS. Red lines represent MTT values. Blue, pink, and green bars are FU, BU, and MO periods, respectively, obtained from MTT abrupt changes for each parameter.

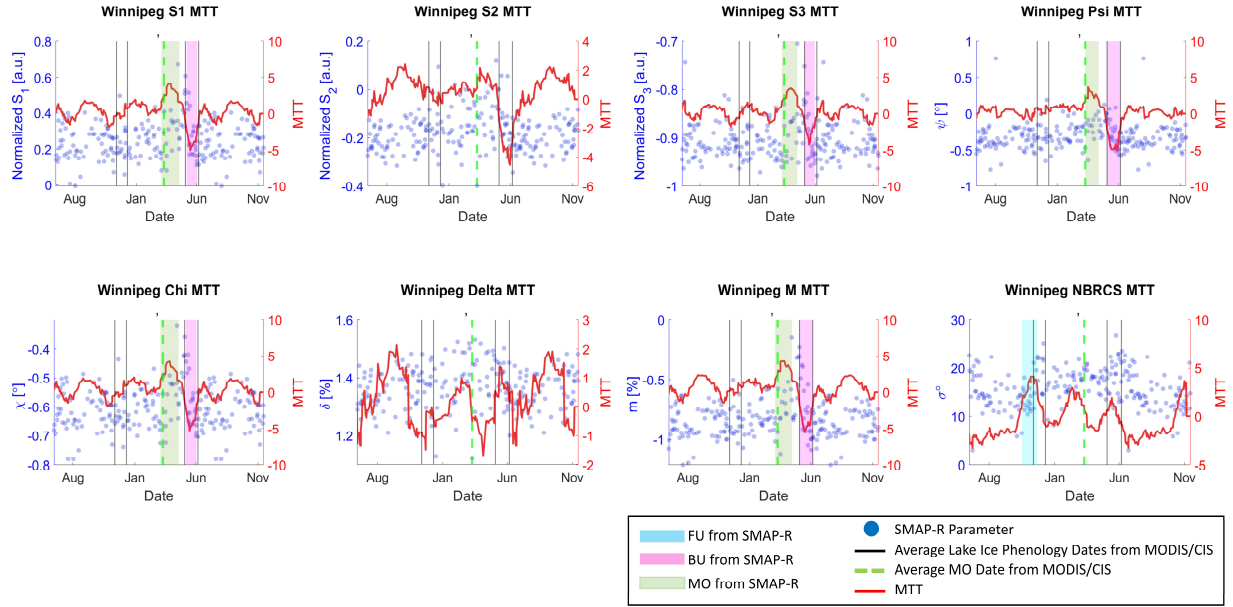


Figure 4-13. Daily SMAP-R data (blue dots) for Lake Winnipeg from October 2015 to December 2022. Black vertical lines represent the average of phenology dates, i.e., BUS, BUE, FUS, and FUE, respectively from left to right. Green dashed lines are the MO time. Phenology and MO lines are obtained from reference sources, i.e., MODIS and ICS. Red lines represent MTT values. Blue, pink, and green bars are FU, BU, and MO periods, respectively, obtained from MTT abrupt changes for each parameter.

As shown in Figures 4-10 to 4-13, except for δ and S_2 , most parameters show sensitivity to BU periods for all lakes so that significant abrupt changes in MTT values are observed close to the MO dates and BU periods, which are shown by green and pink bars in Figures 4-10 to 4-13, respectively. As indicated by Howell et al. (2009), the spring snow melt, which is associated with the increase in temperature during springtime, is linked to changes in the surface conditions of lake ice, leading to a reduction in albedo prior to the onset of the BUS. Figure 4-14 represents a timeframe for each lake comparing the MO and BU periods with the associated dates retrieved from MTT abrupt changes over each parameter. On the other hand, most parameters do not show any sensitivities to the FU periods. However, σ^0 shows significant spikes during FU periods for

three lakes, i.e., GBL, GSL, and Lake Athabasca. Aside from σ^0 , for Lake Athabasca, the MTT analysis of ψ and m shows spikes during the FU period.

Table 4-2. Average FU and BU periods and MO dates for each lake along with MTT abrupt change periods for each parameter associated with the FU and BU periods and MO dates of each lake.

Parameters	GBL	GSL	Athabasca	Winnipeg
FU	30 Oct - 15 Dec	28 Oct - 20 Dec	30 Oct - 17 Dec	11 Nov - 11 Dec
BU	15 Jun - 15 Jul	21 May - 26 Jun	15 May - 14 Jun	3 May - 5 Jun
MO	5 May	21 Apr	13 Apr	11 Mar

S_1	FU	N/A	N/A	N/A	N/A
	BU	31 May - 5 Jul	20 May - 28 Jun	21 May - 16 Jun	7 May - 2 Jun
	MO	14 Apr	12 Apr	11 Apr	5 Mar
S_2	FU	N/A	N/A	N/A	N/A
	BU	N/A	N/A	N/A	N/A
	MO	N/A	N/A	N/A	N/A
S_3	FU	N/A	N/A	N/A	N/A
	BU	28 May - 3 Jul	20 May - 19 Jun	20 May - 16 Jun	4 May - 31 May
	MO	14 Apr	16 Apr	14 Apr	5 Mar
ψ	FU	N/A	N/A	24 Nov - 15 Dec	N/A
	BU	13 Jun - 14 Jul	19 May - 3 Jul	14 Apr - 20 Jun	3 May - 6 Jun

	MO	17 Apr	19 Mar	14 Apr	11 Mar
χ	FU	N/A	N/A	N/A	N/A
	BU	31 May - 5 Jul	20 May - 28 Jun	12 May - 19 Jun	7 May - 2 Jun
	MO	14 Apr	12 Apr	12 Apr	5 Mar
δ	FU	N/A	N/A	N/A	N/A
	BU	N/A	N/A	N/A	N/A
	MO	N/A	N/A	N/A	N/A
m	FU	N/A	N/A	24 Nov - 11 Dec	N/A
	BU	28 May - 3 Jul	20 May - 30 Jun	14 May - 19 Jun	4 May - 6 Jun
	MO	15 Apr	10 Apr	11 Apr	5 Mar
σ^0	FU	2 Nov – 30 Nov	8 Nov - 12 Dec	N/A	17 Oct – 21 Nov
	BU	27 May – 30 Jun	23 May - 13 Jun	29 May - 6 Jun	N/A
	MO	N/A	N/A	N/A	N/A

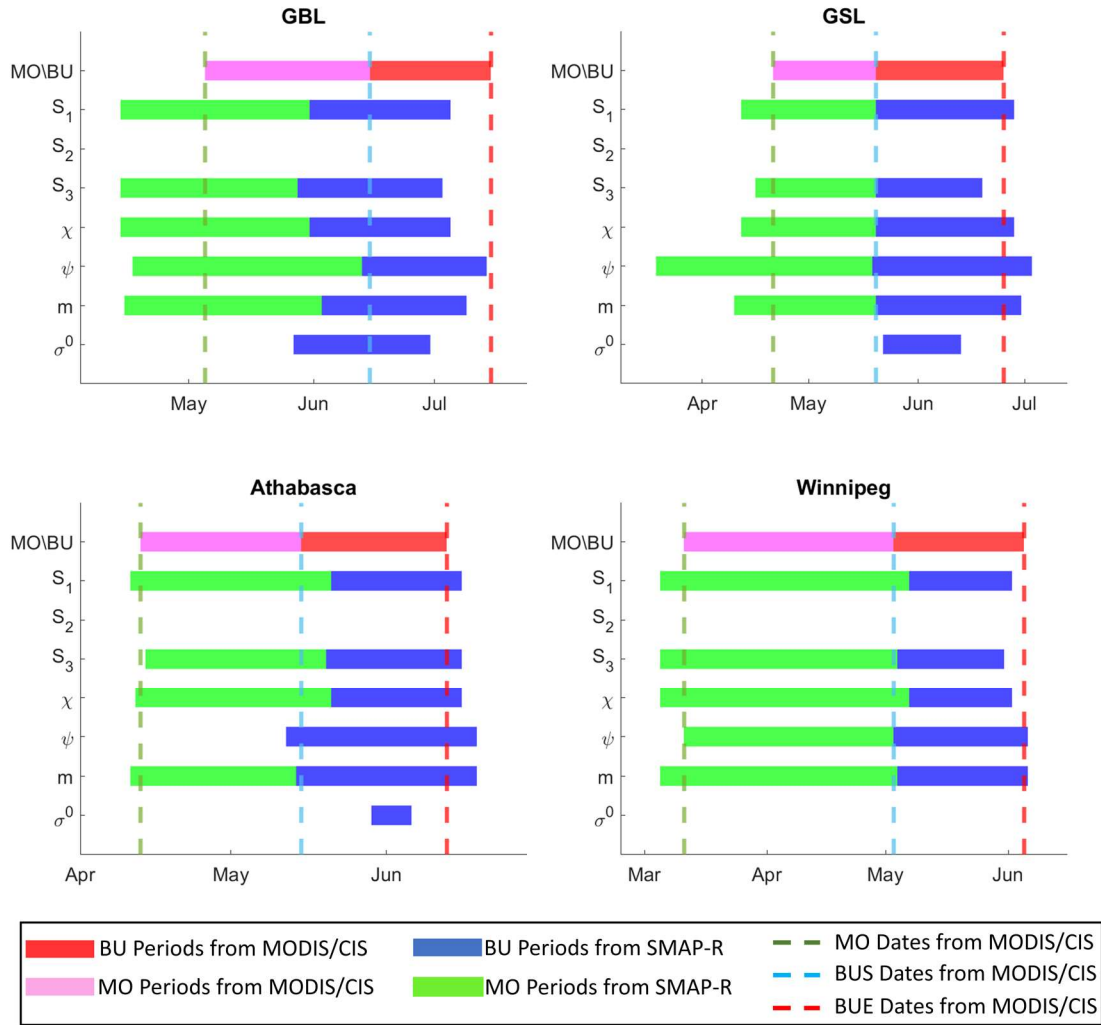


Figure 4-14. Average BU (red bars) and MO (pink bars) periods for each lake compared with the abrupt change periods for each parameter. Vertical dashed are associated to the average MO, BUS and BUE dates.

Based on the timeframes shown in Figure 4-14, for GBL, the abrupt change period of ψ is the most sensitive to the BU period as it starts 2 days before BU and ends 1 day before the average BUE. Other parameters have a two-week shift in retrieving both BUS and BUE, as well as MO. On the other hand, σ^0 , the only parameter sensitive to the FU period, shows a 3 and 15-day discrepancy in retrieving FUS and FUE, respectively, when compared to MODIS/CIS derived dates.

For GSL, all parameters show a very close abrupt change period for BUS. For four parameters, S_1 , S_3 , χ , and m , the difference between the retrieved and observed BUS is 0 day. On the other hand, S_1 and χ show the best performance in BUE retrieval (3 days later). For MO detection, the difference for S_3 is 5 days (earlier), which is the best performance among all other parameters. On the other hand, σ^0 is again the only parameter sensitive to the FU period, with 10- and 8-days discrepancy in FUS and FUE timing, respectively.

For Lake Athabasca, m and χ show the best performance for BUS timing with 1- and 3-days discrepancy (earlier), respectively, while for the BUE timing, S_1 , S_3 , and χ , show the best performance with a difference of 3 days (later). Furthermore, S_1 , S_3 , m , and χ , show a maximum 2 days in the timing of MO for this lake. However, only m and ψ show sensitivity to FUS and FUE with differences of more than 14 days.

For Lake Winnipeg, ψ and m reveal differences of less than 2 days in both BUS and BUE timing. Also, ψ shows no difference in MO timing for this lake. Moreover, for the FU period, σ^0 is the only sensitive parameter with differences of more than two weeks in detecting both FUS and FUE.

4.5. Regression Analysis Using Random Forest for Phenology Timing

In this section, we explore the potential of using regression models to improve the accuracy of lake ice FU and BU timing estimation. Section 4.1 has demonstrated significant correlations between polarimetric parameters from the SMAP-R dataset and lake ice fractions from the CIS. Building on this, we employed a Random Forest (RF) regression approach to combine these polarimetric parameters into a single predictive model for lake ice phenology timing.

We started by normalizing the polarimetric parameters to a range between 0 and 1 to ensure comparability and enhance the model's performance (Akhavan et al., 2021). The normalization was applied to both the training dataset and the new dataset used for prediction. Next, we used the lake ice fraction data from CIS during the FU period as the reference target variable (CIS) for training the RF model. The dataset was split into 80% for training and 20% for testing, from observation of each year. The training involved fitting the RF model to the normalized polarimetric parameters to predict the CIS values. The feature importance scores from the RF model indicated which polarimetric parameters had the highest predictive power for CIS. These scores guided the selection of parameters that were most relevant for estimating FU timing. Figure 4-15 displays the histogram of SMAP-R tracks associated with each lake ice fraction obtained from CIS datasets for all four lakes during BU and FU periods. The RF model's feature importance analysis reveals that parameters such as σ^0 , χ , and ψ had the highest correlations with CIS. Table 4-3 shows the features importance for each lake.

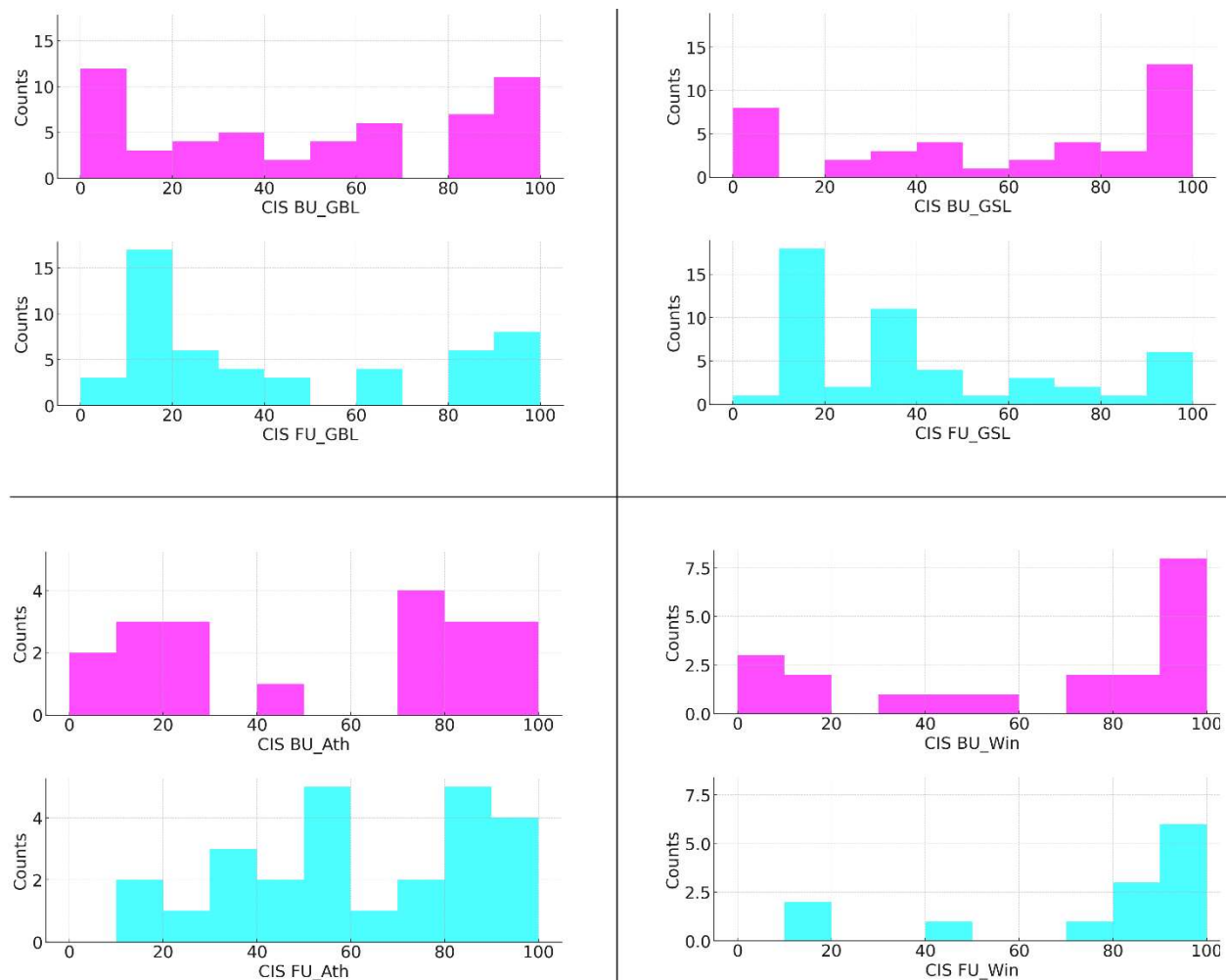


Figure 4-15. Histograms of the number of SMAP-R observations associated to lake ice fractions from CIS during BU and FU for (top left) GBL, (top right) GSL, (bottom left) Lake Athabasca, and (bottom right) Lake Winnipeg.

Table 4-3. RF feature importance during FU periods

GBL		GSL		Athabasca		Winnipeg	
σ^0	0.670084	σ^0	0.378233	σ^0	0.408622	σ^0	0.242797
ψ	0.083749	χ	0.143235	M	0.149981	χ	0.224582
S_3	0.075499	S_1	0.142913	S_2	0.142632	S_1	0.142151
M	0.058636	ψ	0.11521	ψ	0.111086	ψ	0.127132
S_2	0.04326	S_3	0.091153	S_3	0.06294	S_3	0.121013
S_1	0.034738	M	0.070852	S_1	0.062785	M	0.098846
χ	0.034033	S_2	0.058405	χ	0.061954	S_2	0.043479

These parameters were thus identified as key indicators for lake ice presence and FU timing. The newly generated composite parameter was evaluated using the MTT analysis method previously applied to individual polarimetric parameters. Figure 4-16 shows the MTT analysis of the RF output along with the FU period associated to the abrupt change of the MTT of this parameter for each lake. In addition, the retrieved FU periods from the MTT analysis over the RF regressor output along with the actual FU periods are presented in Table 4-4.

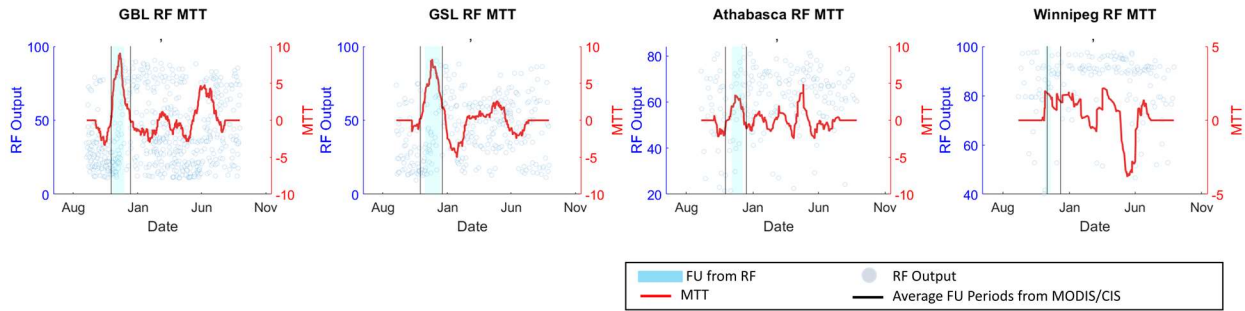


Figure 4-16. MTT of the RF Regressor Output along with FU dates (vertical black lines) and retrieved FU periods (light blue bars) for all 4 lakes.

Table 4-4. Average FU periods for each lake along with the retrieved FU periods from abrupt change in RF MTT for four lakes.

	GBL	GSL	Athabasca	Winnipeg
Average FU	30 Oct -15 Dec	28 Oct - 20 Dec	30 Oct - 17 Dec	11 Nov - 11 Dec
FU from RF	2 Nov - 30 Nov	9 Nov - 16 Dec	13 Nov - 9 Dec	6 Nov - 19 Nov

The integration of multiple polarimetric parameters through the RF regression offers a robust method for enhancing FU timing estimation. By leveraging the strengths of various parameters, the RF-generated composite parameter provides a more reliable indicator of lake ice conditions. According to the parameters' importance scores presented in Table 4-3, σ^0 emerges as the most important parameter for all four lakes during the FU period. This observation aligns with the findings in Section 4.4.2 (Figures 4-10 to 4-13 and Table 4-2), where σ^0 consistently served as the best indicator for FU timing. The higher sensitivity of σ^0 to changes in surface roughness during the FU period underscores its critical role in capturing the dynamics of lake ice formation. This finding is consistent with the previous study by Ghiasi et al. (2023), which used CYGNSS

SNR for lake ice phenology timing. SNR, similar to σ^0 , is highly sensitive to surface roughness, further validating the importance of σ^0 in monitoring lake ice dynamics.

However, the RF model did not perform as well for FU timing analysis for Lake Winnipeg, as shown in Figure 4-16 (leftmost panel) and Table 4-4. This discrepancy can be attributed to the limited number of observations during the FU period, with only 13 tracks available, introducing uncertainties into the training process. Additionally, the temporal distribution of SMAP-R observations over the FU period was inadequate, failing to cover all lake ice fraction bins, as illustrated in Figure 4-15 (bottom left). This lack of comprehensive coverage hindered the training process, causing the RF model to fail in detecting the BU period for Lake Winnipeg accurately.

We also performed the RF analysis on the CIS data during the BU periods. Unlike the FU periods, σ^0 was not consistently the most important feature for all lakes. As shown in Table 4-5, other features such as S_2 and S_3 also demonstrated significant importance depending on the specific lake. The outputs of the RF analysis during the BU periods were comparable to the actual BU periods, as shown in Figure 4-17 and Table 4-6.

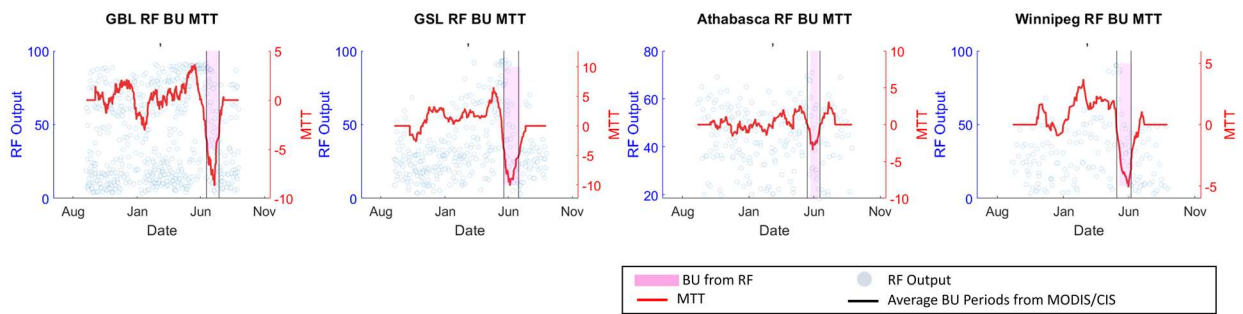


Figure 4-17. MTT of the RF Regressor Output along with BU dates (vertical black lines) and retrieved BU periods (light pink bars) for all 4 lakes.

Table 4-5. RF feature importance during BU periods

GBL		GSL		Athabasca		Winnipeg	
S_2	0.397881	S_3	0.381104	σ^0	0.325657	S_3	0.262548
ψ	0.20105	M	0.328402	S_3	0.196247	S_2	0.171632
σ^0	0.11125	S_1	0.092949	S_2	0.135629	M	0.16883
M	0.104522	σ^0	0.088201	M	0.112151	χ	0.165452
S_3	0.100894	χ	0.054694	ψ	0.091937	S_1	0.125059
χ	0.044022	ψ	0.027377	χ	0.084816	ψ	0.091142
S_1	0.040381	S_2	0.027275	S_1	0.053562	σ^0	0.015337

Table 4-6. Average BU periods for each lake along with the retrieved BU periods from abrupt change in RF MTT for four lakes.

	GBL	GSL	Athabasca	Winnipeg
Actual BU	15 Jun - 15 Jul	21 May - 26 Jun	15 May - 14 Jun	3 May - 5 Jun
BU from RF	12 Jun - 16 Jul	20 May - 30 Jun	23 May - 11 Jun	10 May - 8 Jun

Similar to the FU periods, combining multiple polarimetric parameters using RF regression provides a robust approach to improving BU timing estimation. Utilizing the

individual contribution of each individual parameter, the RF-generated composite parameter serves as a more dependable indicator of lake ice conditions.

4.6. Conclusions

This paper presents the first examination of the sensitivity of full polarimetry GNSS-R signals to lake ice cover fraction and the timing of phenological events. We utilized data obtained from the SMAP-R receiver from October 2015 to December 2022, to capture RHCP GPS signals transmitted in both V- and H-polarizations. Our study involved the analysis of σ^0 , Stokes parameters, and child Stokes parameters. We assessed SMAP-R's response to variations in lake ice cover and its phenology across four Canadian lakes, i.e., GBL, GSL, Lake Athabasca, and Lake Winnipeg. The findings suggest that both Stokes and child Stokes parameters, as well as σ^0 , show sensitivity to physical characteristics of these lakes, exhibiting significant potential for lake ice cover monitoring with correlations reaching up to 0.7. Furthermore, these parameters demonstrate sensitivity to the timing of lake ice phenology and melt onset with uncertainty of less than 5 days for most parameters and lakes. Through regression analysis using Random Forest regression, we combined multiple polarimetric parameters to enhance the accuracy of lake ice phenology timing estimation. The RF model identified σ^0 as the most significant feature during the FU period, highlighting its importance in capturing the dynamics of lake ice formation. However, during the BU period, parameters such as S_2 and S_3 became more important depending on the specific lake, indicating the variability in feature importance across different phenological events. The outputs of the RF model for both FU and BU periods were comparable to actual phenology dates, validating the potential of this approach in lake ice monitoring.

Future research should focus on comparing the behavior of σ^0 with comparable observations from other GNSS-R missions with northern coverage, such as Spire and HydroGNSS, at both grazing angles and conventional modes over northern lakes with different surface conditions. Additionally, there were limitations in the RF analysis due to the lack of observations associated with all lake ice fraction bins. Specifically, the number of observations over Lake Winnipeg during the FU period was limited, introducing uncertainties into the training process. Moreover, the temporal distribution of SMAP-R observations over the BU period did not cover all lake ice fraction bins, which hindered the training process. This lack of comprehensive coverage led to the RF model detecting the BU period for Lake Winnipeg with a high degree of uncertainty. To improve the RF training and subsequent results, acquiring more observations that encompass all lake ice fraction bins would be beneficial. Enhanced observational coverage will aid in refining the model, thereby providing more accurate and reliable estimates of lake ice phenology.

Chapter 5 - Sensitivity of GNSS-R Reflectivity to Lake Surface Conditions

Abstract - This paper introduces a new modelling approach for space-based Global Navigation Satellite System-Reflectometry (GNSS-R) applied to lake surface conditions – open water and lake ice as a multi-layer medium – focusing on two study areas for demonstration purposes: Qinghai Lake, Tibet Plateau, and Great Bear Lake (GBL)/Great Slave Lake (GSL), Northwest Territories, Canada. In the sensitivity experiments, reflected signals were assumed to be acquired by the Cyclone Global Navigation Satellite System (CYGNSS) over Qinghai Lake (incidence angles 70 to 50 degrees) and Spire Grazing Angle (GA) measurements over GBL and GSL (incidence angles 85 to 65 degrees). For CYGNSS, lake ice detection over Qinghai Lake is enabled by the consistent reflectivity of ice, which varies less than 5 dB, compared to the highly variable reflectivity of open water, which is up to 30 dB. For Spire GA, ice consistently shows higher reflectivity than water by 3 to 30 dB, allowing effective lake ice detection over GBL and GSL. Results indicate no sensitivity to ice thickness or on-ice snow depth in both datasets. Simulated reflectivity values from CYGNSS demonstrate a strong sensitivity to surface roughness at lower incidence angles, whereas Spire GA simulated reflectivity show minimal or no sensitivity to surface roughness. This modelling approach provides the foundation for incorporation of a GNSS-R module into the existing Snow Microwave Radiative Transfer (SMRT) model, enabling the model to incorporate exact environmental conditions for each track, allowing direct comparison of modeled and observed GNSS-R reflectivity for specific scenarios.

Keywords: Global Navigation Satellite System Reflectometry (GNSS-R), Cyclone Global Navigation Satellite System (CYGNSS), Spire – Grazing Angle

5.1. Introduction

Lake ice plays a multifaceted and crucial role in both local weather/climates and broader ecological systems, impacting everything from precipitation patterns to transportation networks and recreational activities. As documented in various studies (e.g., Bajinath-Rodino et al., 2018), lakes and their ice cover significantly influence local climate and energy balance. Moreover, the formation of lake ice facilitates essential winter infrastructure like ice roads, which support vital supply lines for industries such as mining. Additionally, lake ice serves as a platform for various recreational pursuits, such as ice fishing and snowmobiling, contributing significantly to local economies during winter months (Cummings et al., 2019). Lake ice cover is recognized as a thematic product of “Lakes” as an essential climate variable (ECV) by the World Meteorological Organization's Global Climate Observation System (GCOS), underscoring its importance as an indicator of climate change (World Meteorological Organization, 2022a; 2022b). Beyond its local impacts, lake ice's influence extends to freshwater ecosystems; its formation affects under-ice biology and ecosystem dynamics (Brown and Duguay, 2010).

Satellite remote sensing has emerged as a crucial tool for studying and monitoring ice phenology, especially considering the decline in ground observations and the increasing importance of understanding the impacts of climate change on ice cover dynamics. Studies have shown a significant decline in ground observations of lake and river ice phenology since the 1980s (Murfitt and Duguay, 2021), coinciding with a warming climate and resulting changes in ice formation and decay patterns (Hewitt, 2019; Lopez et al., 2019). This decline in observations raises concerns about safety risks associated with mid-winter melt events and slushing events, particularly for transportation and recreation on lake ice (Ariano and Brown, 2019). However, remote sensing technologies, including optical, passive microwave, and active microwave, have

gained popularity for monitoring ice phenology and cover extent (Wu et al., 2021; Du et al., 2017; Hoekstra et al., 2020).

A limited number of studies have explored the potential of Global Navigation Satellite System Reflectometry (GNSS-R) L-band signals ($\lambda = 19$ cm) from satellite-based platforms for detecting and monitoring lake ice characteristics. Zavorotny et al. (2020) analyzed raw data from Cyclone Global Navigation Satellite System (CYGNSS), which is the constellation of 8 microsatellites receiving reflected GPS signals at a low elevation orbit, from three specular tracks over Qinghai Lake, Tibet Plateau (China) to investigate the scattering coherency of the lake in both open water and frozen states, noting higher signal-to-noise ratio (SNR) fluctuations in signals reflected from the ice compared to open water, attributed to the lower Fresnel reflection coefficient of the ice layer. Ghiasi et al. (2023) further demonstrated CYGNSS's ability to assess the impact of lake surface conditions (ice and open water) on reflected GNSS signals and determine the timing of lake ice phenology. Their analysis of a four-year time series (August 2018 to August 2022) of SNR values obtained from CYGNSS over Qinghai Lake revealed a significant correlation between abrupt changes in SNR, identified using a moving t-test (MTT), and the occurrence of lake ice phenology events determined from the visual interpretation of MODIS images. More recently, in Chapter 4, we have conducted the first analysis of hybrid compact polarimetric (HCP) GNSS-Reflectometry sensitivity to the physical properties of lake ice, utilizing Soil Moisture Active Passive (SMAP) radar data, demonstrating potential for the monitoring lake-wide ice fraction and ice phenology with high accuracy.

Remote sensing of lake ice involving radiative transfer modelling approaches has become increasingly important for understanding the complex interactions between active/passive microwave signals and ice properties. Initial studies focused on forward modelling of radar

backscatter, examining the influence of bubbles within the ice and roughness at different interfaces, but recent research has emphasized the impact of ice-water interface roughness (Atwood et al., 2015; Tian et al., 2015). Numerical radiative transfer (RT) models have played a significant role in exploring these interactions, including the differences between floating and grounded ice covers of shallow lakes and the effects of various ice properties on SAR backscatter and scatterometer data (Wakabayashi et al., 1994, 1999; Atwood et al., 2015; Matsuoka et al., 1999; Tian et al., 2015). Such models have highlighted the limited influence of tubular bubbles at the ice-water interface on backscatter, underscoring the importance of ice-water interface roughness (Atwood et al., 2015; Tian et al., 2015). Furthermore, recent advancements, such as the utilization of the snow microwave radiative transfer (SMRT; Picard et al., 2018) model, offer a more comprehensive framework for simulating the sensitivity of radar backscatter to variable open water and ice cover conditions, reaffirming the critical role of the ice-water interface in remote sensing of lake ice (Murfit et al., 2022, 2023a, 2023b). These modelling efforts provide valuable insights into the impact of changing ice and open water conditions on radar backscatter, and the possibility of inversions (retrievals) of lake ice cover and lake ice thickness.

In the realm of GNSS-R, previous studies have delved into modelling reflected GNSS signals for various environmental applications. For instance, Loria et al. (2021) emphasized the sensitivity of GNSS-R signals to small-scale surface roughness over inland waters, offering the potential for estimating wave heights and wind vectors. In terms of cryosphere remote sensing, Yan and Huang (2019) modelled the scattering coefficient from sea ice in order to retrieve sea ice thickness using data obtained from TechDemoSat-1 (TDS-1) satellite mission. Furthermore, ground-based GNSS-R modelling has explored snow and sea ice to investigate the influence of multi-layer mediums on reflected GNSS signals (Cardellach et al., 2012; Song et al., 2022).

However, despite these advancements, a critical gap exists in modelling the impact of varied lake surface conditions on GNSS-R signals from current satellite missions, such as CYGNSS and Spire, and in view of upcoming missions like HydroGNSS (Unwin et al., 2021) and Muon Space (2024).

In the absence of previous GNSS-R modelling investigations on lake ice, this study employs a forward model for snow characterization developed by Cardellach et al. (2012) and applied to multilayer surfaces, which considers the total reflectivity and penetration loss in multilayer scenarios. Insights from the coherent scattering model developed by Loria et al. (2021) for CYGNSS measurements are also integrated to consider the roughness loss term as an additional influential factor on GNSS-R measurements from both lake ice (ice-water interface) and open water. The modelling approach presented herein accommodates the complexities of snow and ice mediums by accounting for multi-layered structures, incorporating specified roughness within mediums and across different interfaces. The objective of this study is twofold: 1) to evaluate how the transition between open water and frozen lake conditions alters reflected GNSS signals, with a particular focus on lake ice detection, and 2) to assess the sensitivity of reflected GNSS signals to lake ice properties. The model formulation and simulations performed are described in Section 2, followed by a presentation of results and discussion (Section 3) and a conclusion summarizing the key findings and highlighting activities for future work (Section 4).

5.2. Model Formulation and Simulations

5.2.1. Model formulation

Previous studies have investigated the coherent segment of microwave power bistatically scattered by expansive planar surfaces featuring minor-scale roughness (Zavorotny et al., 2014; Ulaby, 2014). In the case of lake ice, where reflection occurs from a multi-layered medium,

reflectivity (Γ) can be expressed as Γ_T , which is the total reflection coefficient from a k -layer surface. These two latter parameters, i.e., Γ_T and ψ , are dependent on the surface properties, and we aim to model these two parameters for lake ice.

Cardellach et al. (2012) introduced the multiple-ray single-reflection (MRSR) model to explore the power of coherent signals within a multilayer medium. Their model delineates the power of the reflected signal into three primary components originating from the interfaces between air, snow, ice, and water, as depicted in Figure 5-1. According to the MRSR model, the total reflection coefficient (Γ_k) from the bottom of each layer to the receiver is described as follows:

$$\Gamma_k = R_{k,k+1} \prod_{i=1}^{i=k} T_{i-1,i} T_{i,i-1} e^{-2\alpha_i d_i} \psi_k \quad (5-1)$$

where the reflection coefficient is defined as $R = \frac{1}{2}(R_{\parallel} - R_{\perp})$ for LHCP and $R = \frac{1}{2}(R_{\parallel} + R_{\perp})$ for RHCP reflections, $T = \frac{1}{2}(T_{\parallel} + T_{\perp})$ is the transmission coefficient, $\alpha = \frac{2\pi}{\lambda} |Im\{\sqrt{\epsilon}\}|$ is the attenuation coefficient, and d is the distance travelled by the ray inside each layer. In this equation, ψ is the roughness loss term of the reflective surface. The expressions of reflection and transmission coefficients, which are dependent on the dielectric constant ($\epsilon = \epsilon' + \epsilon''i$) and the incidence angle of the ray in each medium (θ), read as follows:

$$R_{\parallel} = \frac{\epsilon_2 \cos \theta_1 - \sqrt{\epsilon_1 \epsilon_2 - (\epsilon_1 \sin \theta_1)^2}}{\epsilon_2 \cos \theta_1 + \sqrt{\epsilon_1 \epsilon_2 - (\epsilon_1 \sin \theta_1)^2}} \quad (5-2)$$

$$R_{\perp} = \frac{\epsilon_1 \cos \theta_1 - \sqrt{\epsilon_1 \epsilon_2 - (\epsilon_1 \sin \theta_1)^2}}{\epsilon_1 \cos \theta_1 + \sqrt{\epsilon_1 \epsilon_2 - (\epsilon_1 \sin \theta_1)^2}} \quad (5-3)$$

$$T_{\parallel} = \frac{2 \cos \theta_1}{\cos \theta_1 + \sqrt{\frac{\epsilon_1}{\epsilon_2} - (\frac{\epsilon_1}{\epsilon_2} \sin^2 \theta_1)^2}} \quad (5 - 4)$$

$$T_{\perp} = \frac{2 \cos \theta_1}{\cos \theta_1 + \sqrt{\frac{\epsilon_1}{\epsilon_2} - \sin^2 \theta_1}} \quad (5 - 5)$$

The ray angle in each of the lower incident mediums can be defined as a function of the incidence angle of the ray to the first layer, based on the Snell's law, as follows:

$$\sqrt{\epsilon_1} \sin \theta_1 = \sqrt{\epsilon_2} \sin \theta_2 \quad (5 - 6)$$

The other surface-dependent parameter, which is surface roughness loss term (ψ), can be characterized by the Rayleigh parameter R_a , as $\psi = e^{-4R_a^2}$, where R_a is written as follows (Loria et al., 2021):

$$R_a = \frac{2\pi|\Delta h| \cos \theta}{\lambda} \quad (5 - 7)$$

where Δh is the root mean square (RMS) of the surface roughness deviation. Therefore, the total reflectivity reflected from a three-layer medium is written as follows:

$$\Gamma_T^2 = \Gamma_1^2 + \Gamma_2^2 + \Gamma_3^2 \quad (5 - 8)$$

It should be noted that the total reflectivity from open water, which is a single layer, is calculated using the simplified version of Equation 5-1, which reads as $\Gamma_T = R_{air,water} \psi_{water}$.

This model seeks to and demonstrate the potential relationship between reflectivity and significant parameters of lake ice, including its presence, under the bistatic configuration. The

model requires several inputs: the freezing state of the lake, the dielectric constant of all four mediums, the thickness of snow and ice layers, the micro-scale roughness at the ice-water interface, and the incidence angle of the GNSS signal. The model output is the surface reflectivity. Figure 5-1 presents a schematic of the implemented modelling approach for GNSS reflected signals from lake ice.

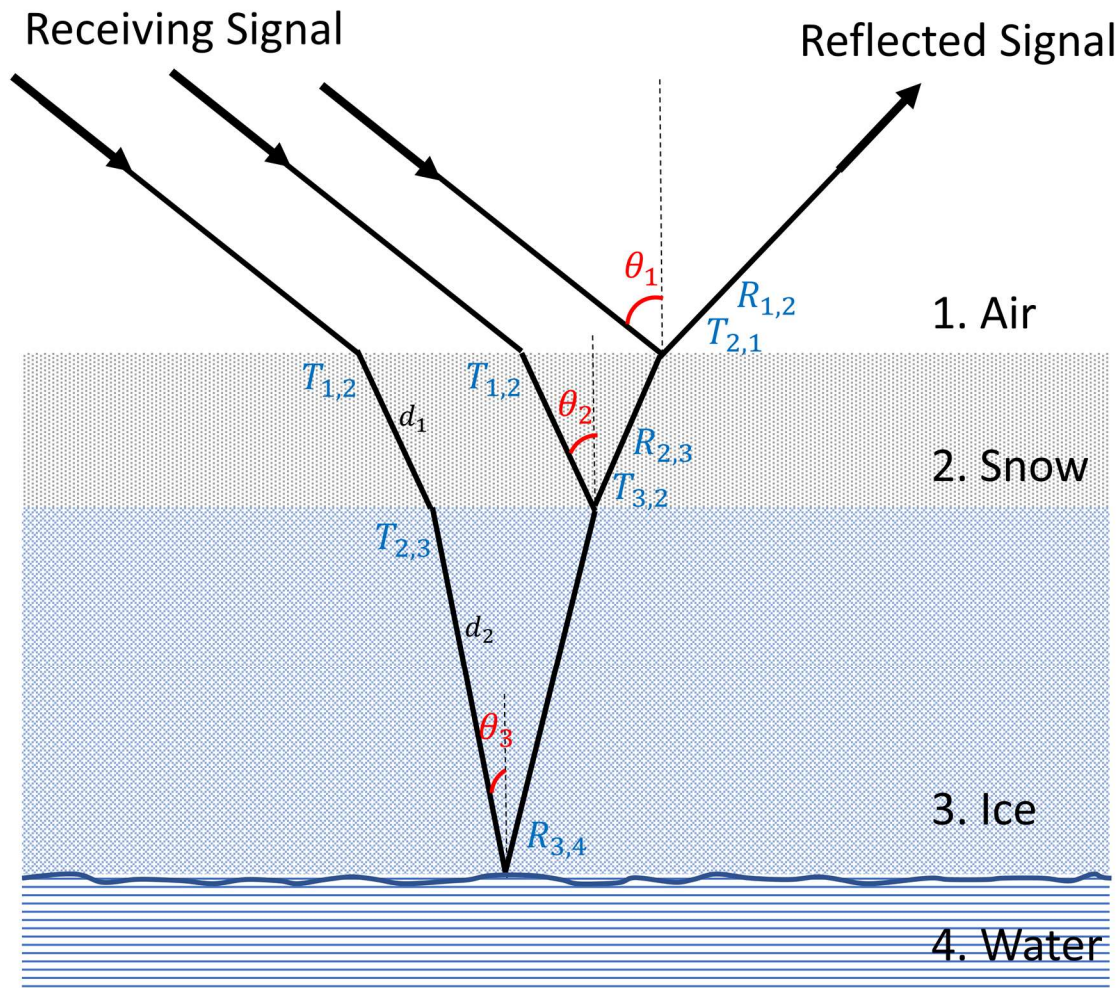


Figure 5-1. Schematic representation of the multi-layered reflectivity model used in this study. The diagram, adapted from Cardellach et al. (2012), illustrates the interaction of the incoming GNSS signal with different layers: air, snow, ice, and water. The signal undergoes reflection (R) and transmission (T) at each interface, with the angles of incidence (θ) changing as the signal passes through different media. The model accounts for the varying dielectric properties of each layer and their impact on the reflected signal received by the GNSS-R system.

5.2.2. Simulations

Through the proposed model, GNSS reflections are simulated using two different lake regions as representative case studies: Qinghai Lake, Tibet Plateau (37° N 100° E) and two large Canadian northern lakes, Great Bear Lake (GBL; 66° N, 121° W) and Great Slave Lake (GSL; $61^{\circ}40'$ N, 114° W). Qinghai Lake, with a surface area of 4,400 km² and seasonal ice cover from December to April, represents weakly saline, mid-latitude lake conditions. In contrast, GBL and GSL, two large freshwater lakes in the Northwest Territories, Canada, feature more extreme seasonal ice dynamics, with complete ice coverage from mid-December to June.

Simulations focus on CYGNSS and Spire GA acquisition modes. The CYGNSS mission operates a constellation of eight satellites in low-Earth orbit, providing global coverage between 38° S and 38° N with left-handed circular polarization (LHCP) signals in the L1 band. In contrast, Spire GA observations are collected at grazing angles (incidence angles above 60°) using right-handed circular polarization (RHCP) signals.

In the case of CYGNSS, simulations focus on Qinghai Lake since it is the only lake that forms a seasonal ice cover within the latitudinal coverage of the satellite constellation (38° S to 38° N). Furthermore, lake ice monitoring for Qinghai Lake has not been evaluated through any GNSS-R mission except CYGNSS (Ghiasi et al., 2023). In contrast, modelling over GBL and GSL is conducted assuming Spire grazing angle (GA) observations, as Spire GAs' northern coverage makes the two sites ideal candidates among high-latitude lakes. Spire GA observations have been previously assessed in northern regions for sea ice monitoring (Nguyen et al., 2023), providing some demonstration for cold region applications. The modelling framework presented herein could

be expanded to simulate GNSS-R observations from other satellite acquisition modes, such as Spire's conventional observations and the upcoming HydroGNSS mission.

For the simulations performed in this study, dielectric constants (relative permittivity values) were derived using SMRT (Picard et al., 2018). The dielectric constants used for Qinghai Lake (salinity 16; Surface Temperature -9°C) were $3.18+0.49i$ for lake ice and $81+25i$ for open water, capturing the weakly saline nature of the lake. For GBL and GSL (salinity 0.5; Surface Temperature -20°C), which consist of freshwater, the lake ice dielectric constant was set to $3.17+0.014i$ and that of the open water $84+13i$. For both lake types, the dielectric constants for air and snow were set to $1+0i$ and $1.76+0.002i$, respectively.

In this study, we delineate the freezing state of a lake into two primary conditions: open water and lake ice. For the simulations, we explore the impact of varied ice and open-water properties on reflectivity by varying lake ice thickness, on-ice snow depth, ice-water interface roughness, open-water surface roughness, and incident angle. For CYGNSS modelling, incidence angles between 70 to 50 degrees are chosen since the majority of CYGNSS observations over Qinghai Lake fall in this range. For Spire GA simulations over GBL and GSL, the incident angles range between 85 and 65 degrees as they are representative of GA observations.

5.3. Results and Discussion

Figure 5-2 presents the modelled surface reflectivity (Γ_T) for lake ice and open water as a function of incidence angle, ranging from 70 to 50 degrees for CYGNSS over Qinghai Lake, and from 85 to 65 degrees for Spire GA simulations over GBL/GSL, across different surface roughness RMS values for ice water interface and for open water. The roughness range for the ice-water interface is selected based on previous modelling studies (e.g., Murfitt et al., 2023a) where this

range is introduced as an average range for ice-water interface roughness. On the other hand, the roughness range for open water (0 to 5 cm) is selected based on previous literature (Loria et al., 2021), which indicates that the coherent component of GNSS reflections is generally retained when surface roughness RMS remains below 4-5 cm. Therefore, reflections from open water with surface roughness RMS greater than 5 cm are consistently lower than those from lake ice and do not impact the modelling. For these reflectivity simulations, ice thickness and snow depth were fixed at 20 cm and 10 cm, respectively because, as will be shown later, lake ice thickness and on-ice snow depth have no impacts on the reflectivity.

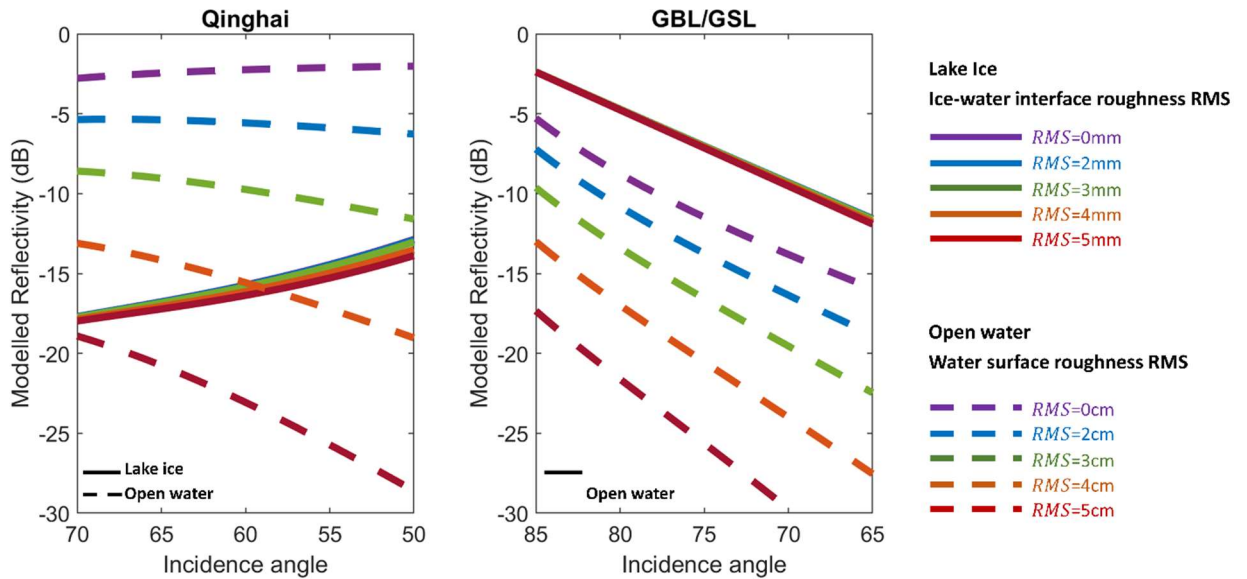


Figure 5-2. Modelled reflectivity as a function of incidence angle for lake ice (solid lines) and open water (dashed lines) with varying surface roughness RMS values.

For CYGNSS simulations over Qinghai Lake, as shown in the left panel of Figure 5-2, open water reflectivity is highly dependent on water surface roughness RMS, while lake ice reflectivity remains relatively stable, changing by only 1 dB as roughness increases from zero to 1 cm. Reflectivity for open water exceeds that of lake ice when the surface roughness is below 3-4 cm; however, when the roughness RMS of open water exceeds 4-5 cm, the coherent reflection

diminishes significantly, as also reported by Loria et al. (2021), resulting in drastically lower reflectivity than lake ice. The model also indicates that open water reflectivity is highly variable due to changes in surface roughness driven by wind, while lake ice reflectivity is more consistent. This consistent reflectivity of lake ice against the high variability of open-water reflectivity was also observed by Ghiasi et al. (2023) over Qinghai. Additionally, lake ice reflectivity increases by up to 5 dB as the incidence angle decreases from 70 to 50 degrees, whereas open water reflectivity generally decreases with decreasing incidence angle. Notably, as observed in a previous study (Loria et al., 2021), increased open-water roughness attenuates signals more rapidly as the incidence angle decreases. As shown in the left panel of Figure 5-2, reflectivity drops by 10 dB as the incidence angle decreases from 70 to 50 degrees at an RMS of 5 cm, while for an RMS of 2 cm, the reflectivity drops by only 1 dB across the same range.

In the right panel of Figure 5-2, which represents Spire GA simulations over GBL and GSL, open water reflectivity similarly drops sharply as surface roughness increases, while lake ice reflectivity consistently remains higher than that of open water. Unlike CYGNSS simulations over Qinghai, the Spire GA simulations show a reduction in lake ice reflectivity by approximately 5 dB as the incidence angle decreases from 85 to 65 degrees. This trend aligns well with findings from Nguyen et al. (2023), where Spire GA observations over sea ice showed a similar decrease in SNR with decreasing incidence angles. Additionally, similar to CYGNSS results, the Spire GA simulations show that increased roughness of open water lowers signals more rapidly as the incidence angle decreases, with reflectivity dropping by 13 dB as the incidence angle decreases from 85 to 65 degrees at an RMS roughness of 5 cm, compared to a 5 dB drop for an RMS of 2 cm across the same range of incidence angle change.

Furthermore, comparing the right and left panels in Figure 5-2 reveals a notable difference in the behavior of ice reflectivity with changes in incidence angle between the two datasets. In the right panel, representing Spire GA (RHCP) observations over GBL/GSL, ice reflectivity decreases as the incidence angle decreases. This trend is expected for Spire GA, as RHCP signals at grazing angles (high incidence, low elevation angles) generally have low penetration through the ice and the ice-water interface, resulting in most reflections coming from the top of the ice surface itself (Nguyen et al., 2023). Therefore, higher reflectivity from lake ice can be similarly expected at a higher incidence angle. Conversely, in the left panel for CYGNSS (LHCP) over Qinghai Lake, ice reflectivity increases as the incidence angle decreases. This behavior aligns with findings from previous studies, which indicate that LHCP signals can penetrate through ice and snow layers, with the reflection primarily occurring at the ice-water interface, thus dominating the overall return signal (Li et al., 2018; Mayers and Ruf, 2018). Consequently, the decrease in incidence angle results in an increase in ice reflectivity, a pattern that has also been observed and modelled by Belmonte-Rivas (2007).

Our analysis demonstrates that it is possible to distinguish between lake ice and open water using GNSS-R observations due to their contrasting reflectivity patterns. For CYGNSS, the consistent reflectivity observed for lake ice compared to the high variability over open water allows for effective differentiation between these two surface states. In contrast, for Spire GA observations, lake ice shows higher reflectivity than open water, making it possible to identify frozen and unfrozen conditions. These distinctions demonstrated through simulations are vital for understanding and monitoring seasonal transitions in lake ice coverage from GNSS-R. Having established the ability to differentiate between ice and open water, we now proceed to evaluate the

impact of other features of lake ice on reflectivity, including lake ice thickness, on-ice snow depth, and ice-water interface roughness.

Figure 5-3 displays the simulated surface reflectivity (Γ_T) against lake ice thickness, where the thickness was increased from 0 to 1 m. The model scenario includes incident angles of 70, 65, 55, and 50 for CYGNSS conventional GNSS-R simulations over Qinghai Lake and incident angles of 85, 80, 75, and 70 for Spire GA simulations over GBL and GSL with the ice-water interface roughness RMS values of 0, 0.3, 0.7, and 1 cm. Simulations show minimal or no sensitivity of reflectivity to changes in lake ice thickness at any incidence angle or ice-water interface roughness RMS, attributed to the L-band's longer wavelength. The simulations are consistent with results from a prior study that modelled L-band SAR backscatter from lake ice (Murfit et al., 2023a). Similar results are achieved when a snow layer is added atop the lake ice. These findings are also attributed to the longer wavelength of the L-band relative to snow grain and possibly underlying ice radii, as supported by L-band backscatter simulations over snow-covered lake ice (Murfit et al., 2023a). Our main simulation results suggest that it is unlikely that freshwater (lake) ice thickness can be retrieved from GNSS-R reflectivity measurements.

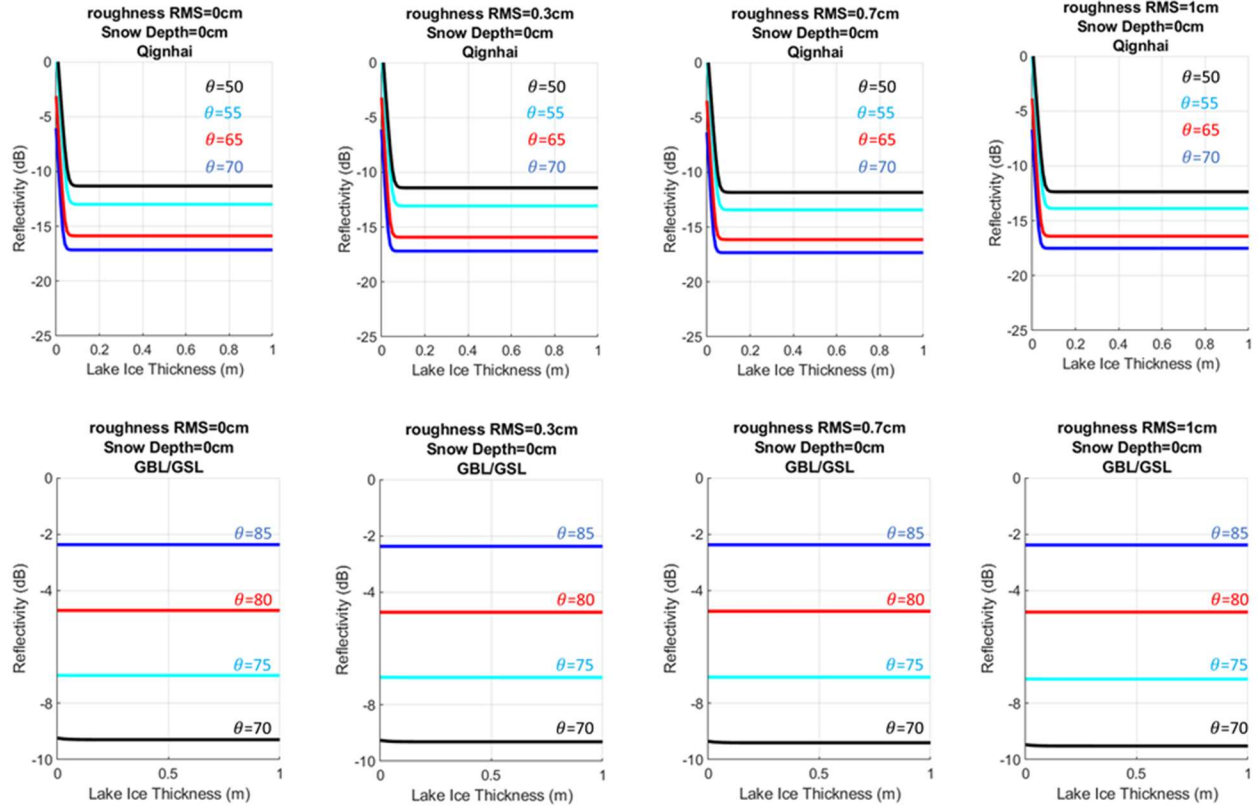


Figure 5-3. Modelled reflectivity as a function of lake ice thickness for various ice-water interface roughness RMS values (0 cm, 0.3 cm, 0.7 cm, and 1 cm) for (top) CYGNSS measurements over Qinghai Lake at incidence angles 50°, 55°, 65°, and 70°, and (bottom) GA measurements over GSL at incidence angles 70°, 75°, 80°, and 85°

Figure 5-4 illustrates the modelled surface reflectivity versus ice-water interface roughness RMS, which progressively increases from 0 to 20 mm, for incidence angles of 70, 65, 55, and 50 for CYGNSS modelling over Qinghai Lake, and incident angles of 85, 80, 75, and 70 for Spire GA simulation over GBL and GSL. For ice-water interface roughness RMS, we selected a wider range (0 to 20 mm instead of 0 to 10 mm used in Figure 5-2) to better illustrate the impact of ice-water interface roughness on the lake ice reflectivity pattern. For this simulation, similar to Figure 5-2, we adopted fixed values of 20 cm for ice thickness and 10 cm for snow depth. For CYGNSS simulation over Qinghai Lake, an increase in ice-water interface roughness generally results in a lower reflectivity across all incident angles, while no significant

changes can be seen in that of Spire GA over GBL and GSL. For CYGNSS simulations over Qinghai Lake, within this 20 mm of roughness alteration, the modelled reflectivity at the incident angles of 50 and 55 degrees decreases by approximately 4 dB and 3 dB, respectively. For the other modelled incident angles, i.e., 65 and 70 degrees, the reductions are 2 dB and 1 dB, respectively, indicating a more gradual decline in reflectivity as the ice-water interface roughness increases, especially at higher incidence angles.

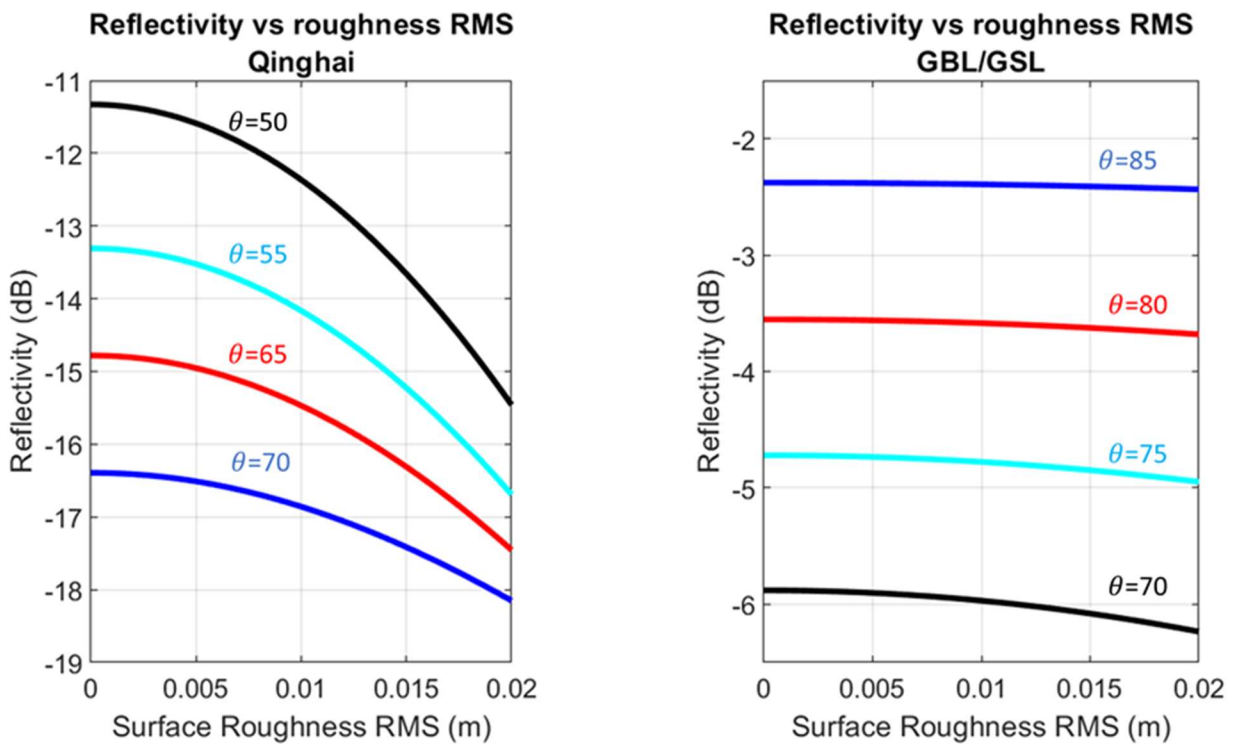


Figure 5-4. Modelled surface reflectivity as a function of ice-water interface roughness RMS for different incidence angles 50°, 55°, 65°, and 70° for CYGNSS over Qinghai Lake (left) and incidence angles 70°, 75°, 80°, and 85° for Spire GA observations over GBL and GSL.

For the CYGNSS simulations, the decrease observed in reflectivity can be attributed to the bistatic configuration of GNSS-R, which contrasts with the monostatic configuration typical of Synthetic Aperture Radar (SAR) methods in remote sensing. In monostatic systems, the receiver is co-located with the transmitter and captures backscattered signals from the surface. In such

configurations, an increase in ice-water interface roughness typically leads to an increase in backscatter due to enhanced scattering. However, in GNSS-R, where the receiver is positioned on the opposite side of the transmitter, the increase in ice-water interface roughness causes a decrease in the reflectivity towards the receiver. This is because the rougher surface scatters the reflected signal more diffusely, reducing the coherent signal strength received by the bistatically positioned GNSS-R receiver. This behavior is clearly reflected in Figure 5-4, where all modelled angles show a consistent decrease in reflectivity with increasing ice-water interface roughness.

5.4. Conclusion

This study developed the first sensitivity analysis and modelling approach for space-based GNSS-R applied to lake ice as a multi-layer medium, focusing on two study areas and two types of observations: Qinghai Lake for CYGNSS observations and GBL/GSL for Spire GA observations. The model showed that for CYGNSS, open water reflectivity is highly variable (up to 30 dB variations across all incidence angles and water surface roughness RMS values) due to surface roughness and can be either higher or lower than that of ice, while lake ice reflectivity remains more consistent (varying by less than 5 dB across all roughness RMS values and incidence angles). This stability in lake ice reflectivity enables lake ice detection over Qinghai Lake using CYGNSS observations as previously reported by Ghiasi et al. (2023). In contrast, for Spire GA, ice consistently shows higher reflectivity than water, with differences ranging from 3 to 30 dB depending on the water surface roughness, allowing for effective lake ice detection over GBL and GSL. Results showed no sensitivity to ice thickness or snow depth for both GNSS-R data types. Additionally, simulated reflectivity values from CYGNSS at lower incidence angles were strongly influenced by ice-water interface roughness, while Spire GA simulations showed minimal to no sensitivity to ice-water interface roughness. Furthermore, our model shows that reflectivity values

from the CYGNSS simulation decrease as the incident angle increases, while those from the Spire GA simulations increase as the incident angle increases.

A key direction for future validation efforts will also involve using specific tracks from GNSS-R datasets, such as Spire and upcoming missions like HydroGNSS and Muon Space, to enable precise, scenario-based simulations over northern lakes. With known dates and locations for GNSS-R observations, detailed in-situ data—including lake ice thickness, snow depth, temperature, wind speed and direction, humidity, and dielectric constants—can be collected. This information will allow the model to be updated with precise environmental conditions for each specific track, generating modelled reflectivity for a given scenario that can be directly compared with actual GNSS-R observations from the same time and location. Such targeted validation will refine the model's accuracy and enhance our understanding of GNSS-R's capabilities in monitoring lake ice conditions. Additionally, integrating GNSS-R modules into comprehensive radiative transfer models such as SMRT (Picard et al., 2018) coupled with a lake ice model as done in recent imaging SAR backscatter investigations (Murfitt et al., 2023a,b), offers a promising path forward, potentially improving the accuracy of lake ice and other cryospheric monitoring across diverse regions. Future work should apply this enhanced model to a broader range of GNSS-R datasets, including those from HydroGNSS and Muon Space, to further validate its robustness and adaptability.

Chapter 6 – Conclusion

6.1. Summary

Chapter 2 establishes the fundamental principles of GNSS-R and its cryosphere applications, particularly in the context of lake ice. It provides a comprehensive overview of GNSS, emphasizing their role in positioning and remote sensing applications. The chapter explains the concept of GNSS-R, detailing how reflected signals can be used to extract valuable geophysical information. A significant portion of the chapter is dedicated to discussing the scattering mechanisms of GNSS signals when they interact with lake ice, including the influence of the dielectric properties of ice on signal reflection. The chapter also reviews previous applications of GNSS-R in cryosphere remote sensing, highlighting its potential for monitoring lake ice cover and phenology. The theoretical groundwork laid in this chapter is critical for understanding the subsequent analyses presented in the thesis.

In Chapter 3, the potential of GNSS-R, specifically CYGNSS, for monitoring lake ice phenology on Qinghai Lake is extensively evaluated. Using four ice seasons' worth of data, the study applied a moving t-test algorithm to detect FU and BU periods based on changes in SNR values. The results were validated against MODIS imagery, providing an in-depth analysis of the timing of critical events such as FUS, FUE, BUS, and BUE. Regarding accuracy, CYGNSS-derived ice phenology timings exhibited an MBE of 6 days for FUS and -4 days for FUE, and MAE of 7 and 5 days, respectively, when compared to MODIS data. During the breakup period, CYGNSS detected BUS was 10 days earlier than MODIS (MBE = -10 days; MAE = 10 days), while the BUE was determined with an MBE of -4 days and an MAE of 4 days. The overall accuracy of ICD between CYGNSS and MODIS showed an MBE of 0 days and an MAE of 5 days. The sensitivity of CYGNSS to spring melt onset was also notable, with the SNR values

demonstrating significant fluctuations up to 13 days before the actual breakup started, as indicated by MODIS. This allowed the detection of the beginning of melt, proving the capability of GNSS-R for high-resolution monitoring of lake ice dynamics. These findings highlight the robustness of CYGNSS in capturing lake ice transitions, albeit with some uncertainties due to environmental factors like wind speed over open water and snow accumulation on the ice surface that could introduce variations in SNR.

In Chapter 4, the study focuses on the sensitivity of Hybrid Compact Polarimetry (HCP) GNSS-R parameters obtained from SMAP-R to lake ice surface conditions and lake ice phenology across four Canadian lakes: GBL, GSL, Lake Athabasca, and Lake Winnipeg. Several key parameters, including the Stokes and child Stokes parameters, as well as NBRCS, were analyzed for their correlation with lake ice fraction and the accuracy of FU and break-up BU timing. For the FU periods, the lake ice fractions from CIS showed the highest correlations with σ_0 , with values ranging from 0.33 to 0.63 across the four lakes. Similarly, S1 and χ demonstrated a high cross-correlation of over 0.99 for all lakes during FU. During BU periods, the correlation patterns changed, with GBL showing the highest correlation between lake ice fraction and S2 (0.63), while GSL had the highest correlation with χ and S3 (0.72), highlighting the variability in parameter sensitivity depending on the phenological stage and the lake. Additionally, the implementation of RF regression models significantly improved the accuracy of ice phenology timing. The RF models identified NBRCS as the most critical parameter for FU periods, while S2 and S3 became more important during BU periods. The RF model provided estimates with less than 5 days of uncertainty for most phenology events. For instance, the BU period for GSL was predicted with a 0-day difference compared to observed values, while Lake Athabasca had 1–3 days of uncertainty for BUS timing. The study highlights the potential of HCP GNSS-R for lake ice monitoring and

phenology analysis, achieving strong correlations and improved accuracy through machine learning approaches like RF regression. This analysis confirms the value of multi-parameter regression models in enhancing the detection and monitoring of lake ice phenology.

In Chapter 5, the study presents a multi-layer scattering regime model designed to simulate the sensitivity of GNSS-R reflectivity to lake surface conditions, focusing on CYGNSS observations over Qinghai Lake and Spire GA observations over GBL and GSL. The model incorporates key parameters, including ice thickness, snow depth, surface roughness, and incidence angles, to assess their impact on reflectivity. Results indicate that GNSS-R reflectivity is sensitive to surface roughness, particularly for CYGNSS, where open water reflectivity shows significant variability (up to 30 dB) due to roughness changes, while lake ice reflectivity remains more consistent, with variations below 5 dB. This stability in lake ice reflectivity facilitates ice detection over Qinghai Lake. For Spire GA, ice consistently displays higher reflectivity than water, with differences between 3 and 30 dB depending on roughness, enabling reliable ice detection over GBL and GSL. The model revealed no sensitivity to ice thickness or snow depth in both GNSS-R datasets, underscoring the predominant role of surface roughness and incidence angle. Although preliminary validation shows alignment with general observational patterns, comprehensive validation requires in-situ data on specific environmental conditions at GNSS-R track locations. Overall, this chapter demonstrates GNSS-R's potential to improve lake ice monitoring and provides a framework that could be integrated into SMRT for broader applications across cryospheric environments.

6.2. Limitations

The primary limitation of GNSS-R for lake ice observations lies in its reliance on simplified scattering models for GNSS signals interacting with lake ice. In GNSS-R, one mostly

assumes a single-scattering regime, which may not fully capture the complex interactions between GNSS signals and multi-layered ice structures. This simplification could lead to inaccuracies in the BRCS estimation, particularly in scenarios where multiple scattering events or significant surface roughness are present. Additionally, the theoretical models discussed do not account for the heterogeneity of lake ice, which could introduce variability in the signal reflection that is not addressed in this chapter.

Chapter 3's analysis is constrained by the assumption that GNSS signals primarily reflect from the ice-water interface, with limited consideration given to the potential for multiple reflections from other layers, such as snow or ice deformation. This assumption could introduce errors in the interpretation of SNR values, particularly in complex ice conditions where multiple scattering regimes are likely. The study's focus on a single geographical area—Qinghai Lake—limits the generalizability of the findings to other regions with different climatic and environmental conditions. Additionally, the chapter does not fully address the potential impact of snow cover on the accuracy of ice phenology detection, which could be a source of error in regions with heavy snowfall and potential for slushing and snow ice formation. The validation against MODIS data, while useful, is also limited by the resolution and accuracy of the MODIS-derived phenology dates, particularly under cloudy conditions.

The limitations of Chapter 4 stem from the challenges associated with hybrid compact polarimetry in GNSS-R, particularly in differentiating between frozen and open water conditions under varying environmental circumstances. The study's reliance on SMAP-R data, while innovative, introduces potential biases related to the spatial and temporal resolution of the observations. The regression analysis using Random Forest models, although effective, may not fully capture the complexity of the interactions between the GNSS signals and the ice surface,

leading to potential inaccuracies in the determination of phenology timing. Furthermore, the study is limited to four Canadian lakes, which may not be representative of other regions with different ice cover dynamics. The chapter also acknowledges the difficulty of isolating specific reflective layers in the presence of snow or wet ice, which could affect the interpretation of the polarimetric data.

Chapter 5 primarily focuses on simulating the sensitivity of GNSS-R reflectivity to lake surface conditions. This model is generally consistent with current observations; however, full validation is left for future work. Once we have access to precise environmental data for each specular point, including lake ice thickness, snow depth, temperature, and precipitation at each observation date and location, we will be able to simulate reflectivity for those exact points and compare it directly with actual GNSS-R observations. In addition, the current model is based on idealized conditions, representing lake ice with a simplified four-layer structure of air, snow, ice, and water, which may not fully capture the natural complexity of lake ice and water interfaces. This approach does not yet account for additional potential layers or variable properties within the lake ice and snow, such as differing densities, water content, or dielectric constants, all of which could impact reflectivity.

6.3. Future Directions

Future research should focus on expanding the GNSS-R experiments to a wider range of geographical regions with different ice conditions to validate the technique's applicability beyond Qinghai Lake. There is also a need to explore the impact of snow cover (depth, density and layering) and other environmental factors on the accuracy of ice phenology detection, potentially incorporating higher-frequency GNSS signals to improve measurement precision. Further development of the theoretical models used in GNSS-R, particularly those addressing multi-

layered ice structures and complex scattering regimes, would enhance the robustness of the technique. Additionally, integrating GNSS-R data with other remote sensing data sources, such as Synthetic Aperture Radar (SAR), could provide a more comprehensive understanding of lake ice dynamics.

Furthermore, future studies should investigate the potential of hybrid compact polarimetry in GNSS-R for continuous, real-time monitoring of lake ice phenology across multiple ice seasons and different lake environments. The integration of SMAP-R data with other polarimetric datasets could improve the accuracy and reliability of ice cover detection, particularly in regions with complex ice dynamics. Additionally, research should explore the use of advanced machine learning algorithms, such as deep learning, to enhance the interpretation of polarimetric GNSS-R data and improve the precision of phenology timing. Expanding the analysis to include a broader range of lakes with varying climatic conditions would also help to generalize the findings and validate the technique's applicability across different environments.

In addition, future directions should focus on refining the multi-layer scattering regime model to better account for the complex interactions between GNSS signals and the lake ice and water interface. This could involve the development of more sophisticated algorithms to model the dielectric properties of ice in varying environmental conditions, as well as the incorporation of additional scattering mechanisms to improve the accuracy of the reflectivity predictions. There is also a need to further validate the model against a broader range of observational data from different GNSS-R missions and geographical regions. Integrating the GNSS-R model into the SMRT framework could provide valuable insights for broader cryospheric applications, particularly in the context of global climate monitoring. Additionally, collaboration with ongoing

and future spaceborne GNSS-R missions, such as Spire and HydroGNSS, respectively, could provide a wealth of data for further model refinement and validation.

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