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# Snow Depth Measurement using GNSS-R Techniques: A Review

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***Abstract*— *Snow is a widespread atmospheric constituent on Earth, as well as one of the cryosphere's most important seasonal and inter-seasonal fluctuations. Estimating the amount of snow in hilly areas is essential for a variety of socioeconomic endeavours and environmental research. Traditional methods for monitoring snow depth include accessibility, expense, and coverage limits, especially in isolated and difficult terrain. Global Navigation Satellite System-Reflectometry (GNSS-R) technology has emerged as a promising tool for remote sensing applications that include snow depth estimation. This review study synthesises and evaluates current literature on the use of GNSS-R technology for snow depth retrieval, concentrating on its potential and constraints in various mountainous places around the world. The paper includes a detailed explanation of GNSS-R working principles and receiver's advancement, snow depth retrieval methods using both traditional and remote sensing methods like active microwave, passive microwave, GNSS-R integrating with machine learning and deep learning models to develop a snow depth assessment in diverse geographical contexts. GNSS-R technology aids in snow depth retrieval through Signal-to-Noise Ratio (SNR) and carrier phase pseudorange methods, with optimal choice based on application requirements, accuracy, environmental conditions, resources, and complexity-precision trade-offs. The review study aims to provide a comprehensive understanding of the advances in GNSS-R-based snow depth estimation, as well as insights and guidance for future advancements in this field, particularly in addressing the complexities of snow depth estimation in diverse terrains such as those found in India..*

## I. INTRODUCTION

Snow is one of the most extensively dispersed atmospheric constituents on Earth, as well as one of the cryosphere's most significant seasonal and inter-seasonal fluctuations. It is the principal source of water in many parts of the planet. It is vital to global climate variability and hydrological cycles. The amount of snow that falls varies. Snowfall is heavier at higher elevations, and snowpack varies greatly over the landscape. Snow, once on the ground, can be transported by wind, avalanches, and sloughing. As a consequence, high-precision and quick gathering of snow depth data benefits not only human safety, snow disaster avoidance, and hydrological research progress but also monitoring changes in the natural environment. The most essential measure for hydrological analysis is snow-water equivalence (SWE). SWE represents the volume of water potentially available for discharge. Forecasting the rate of snowmelt and evaluating the water content of the snowpack is essential for managing water supply and flood control systems. These variables are critical for forecasting the timing and amount of water released from snowpack, which can help avert flooding and provide a consistent water supply.

Snow depth has historically been monitored through manual measurement or with certain sophisticated sensors on the ground [1]. These approaches give precise assessments of snow depth, but they are either costly or have a limited temporal and geographical resolution. Snow cover area (SCA), snow depth, and SWE are all estimated using satellite and aerial remote sensing systems. In general, satellite estimates provide better consistency in time and distance than ground-based measures. SCA at a medium resolution may be obtained using optical data [2], [3]. Cloud cover, on the other hand, makes measuring snow depth more difficult. Large-scale, very accurate snow depth measurements have been transformed by ground-based LiDAR technology. These technologies, however, are still costly, hardly automated, and frequently need bare-earth terrain elevation measurements [4]. Active and passive microwave methods are also employed to estimate snow depth and SWE. Microwave retrieval is difficult in several ways. When compared to snow fluctuations, passive approaches have a significantly big geographical footprint. Both methods are affected by uncertainties in snow size distribution and upper and lower snow characteristics [5].

Remote sensing technologies have not consistently generated accurate estimations of snow depth or SWE across time. This has led to a growing demand for technology capable of not only accurately retrieving snow depth with higher temporal resolution but also covering larger geographical extents. Reflected GNSS signals have been claimed to offer useful information on the composition of the land surface during the last decade, including snow depth, lake ice thickness, soil moisture content, electrical characteristics of the ground, and sea ice conditions. Jacobson was among the first to propose the use of GPS L1 frequencies for measuring dry snow density [6]. In addition, Larson worked on estimating dry snow density using a GPS multipath signal, suggesting that snow depth can also be estimated using SNR time series, which includes direct as well as reflected signal elements [7]. In the past few years, GNSS reflectometry, a novel approach based on GNSS-reflected signals, has been developed to assess physical and geometric characteristics around the antenna [7], [8]. Using current GNSS station networks and sampling across a 1000 m2 region surrounding the antenna, this strategy may give continuous snow depth monitoring in a global reference frame [9], [10]. The proliferation of GNSS Continuously Operating Reference Stations (CORS) worldwide, particularly in snow regions, has further facilitated the application of GNSS data for snow depth determination [11]. Consequently, GNSS-R-based snow depth calculation offers an economical option capable of achieving high temporal and spatial resolution.

The paper is further organized as follows: in Section 2, a detailed explanation of GNSS-R working principles and receiver's advancement. In section 3, snow depth retrieval methods have been discussed both traditional and remote sensing methods. In section 4, the study is concluded with the potential and challenges of utilizing GNSS-R technology for snow depth retrieval in the diverse and challenging terrains of India.

## II. GNSS-R

Global Navigation Satellite Systems (GNSS) is a network of satellites that provides positioning, navigation, and timing information (PNT) to users worldwide. The system works by continuously transmitting signals from multiple satellites to receivers on Earth. The fundamental principle underlying GNSS operation is trilateration. The best-known GNSS is the Global Positioning System (GPS) operated by the United States, but there are also other systems like GLONASS (Russia), Galileo (European Union), BeiDou (China), QZSS (Japan) and NavIC (India), each offering its unique set of capabilities and coverage. In addition to its core PNT function, GNSS radio occultation may detect the atmosphere and compute tropospheric relative humility as well as ionospheric total electron content. [12]. GNSS reflectometry (GNSS-R) is the alternative type, which encompasses GNSS interferometric reflectometry (GNSS-IR) that leverages signals reflected off the Earth's surface to gather valuable environmental data. Unlike traditional GNSS receivers, which rely solely on direct signals from satellites, GNSS-R receivers analyze signals that bounce off various surfaces, such as land, water bodies, and ice, providing insights into surface characteristics and environmental parameters. The reflected signals carry signatures indicative of surface characteristics, such as roughness, moisture content, and vegetation density, among others. By analyzing these signatures, GNSS-R can provide insights into a wide range of environmental parameters, including soil moisture, sea surface height, snow depth, and vegetation health. Land and sea surface information can be inferred using GNSS-R [13], [14], [15] . Additionally, snow depth data and sea ice parameters have been computed using GNSS-R [16], [17], [18]. The Global Navigation Satellite System-Reflectometry (GNSS-R) idea was introduced by Hall and Cordey [19], and since then, it has been effectively used for a variety of remote sensing applications. It is also one of the main areas of research for remote sensing. Despite multipath signals often being suppressed in high-accuracy applications due to their potential for introducing inaccuracies [20]. Nonetheless, multipath signals carry an abundance of geophysical data that is valuable for GNSS-R systems. The GNSS antenna receives data on the signal-to-noise ratio (SNR), which is crucial for GNSS-R technology as well as signal intensity caused by direct and reflected signal interference. Martin Neira discovered the signal interference occurrence among the direct and reflected signals [21]. SNR power spectrum maps were proposed by Bilich and Larson for multipath evaluation. SNR is therefore mapped with a multipath scenario [22].

2.1 Working and Principles

GNSS-R operates as a bistatic radar technique utilizing signals from GNSS satellites like GPS, GLONASS, Galileo, BeiDou, QZSS, or NavIC to reflect off various surfaces. This technique is grounded in radar and remote sensing principles. GNSS-R relies on the reflection of GNSS signals from diverse surfaces, including the Earth's surface, oceans, ice, buildings, and vegetation. When a GNSS signal comes into contact with a reflecting surface, a portion of the signal is scattered back into space. These reflected signals change phase, amplitude, and polarization as they interact with different surface types and conditions. When a reflected signal returns to a GNSS-R receiver, it contains information about the signal propagation delay (the amount of time it takes for the signal to travel to the reflecting surface and back) and the Doppler shift (the frequency change resulting from the motion of the reflecting surface), forming a Delay-Doppler map. The power gathered by a GNSS receiver following the GNSS signal's scattering throughout the surface of the Earth is referred to as a Delay-Doppler map [23], [24]. The sensing footprint for a specific SNR trace is defined as the First Fresnel zones at various elevation angles. As the satellite elevation angle (e) changes, the First Fresnel zone fluctuates accordingly. Precisely, as the satellite ascends, the Fresnel zone moves nearer to the antenna and diminishes in size. [25].

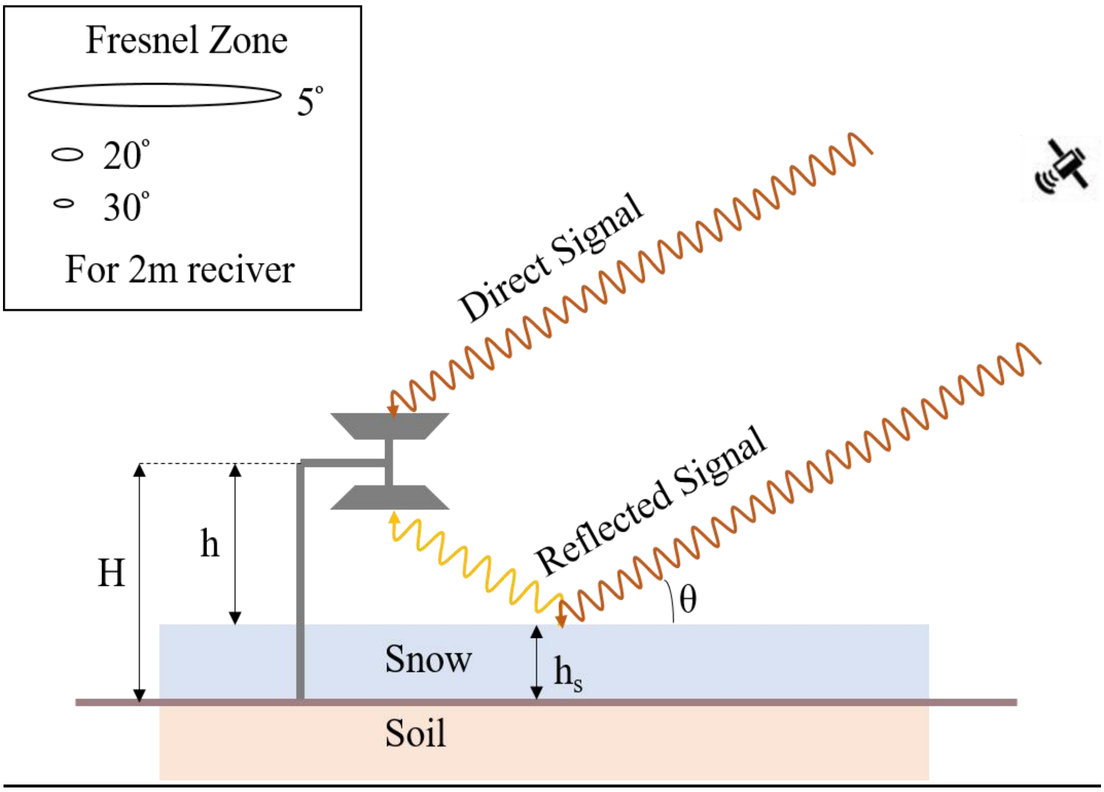


*Fig.1. Working of GNSS-R.*

After a reflection polarisation change, GNSS signals undergo a polarization change: direct signals become Right Hand Circularly Polarized (RHCP), while reflected signals become Left Hand Circularly Polarized (LHCP), as illustrated in Figure 1 [26]. Interference between direct and reflected signals on SNR data indicates signal quality. GNSS user antennas have dual polarisation, RHCP for direct signals, and LHCP for reflected signals. Each polarization is associated with its unique radiation pattern, designed to optimize the reception of RHCP signals (high gain) for omnidirectional acquisition while minimizing antenna sensitivity to LHCP signals (low gain).

In general, the gain for RHCP signals tends to be greater than that for LHCP signals for elevation angles greater than about 10-15 degrees. These disparities, however, reduce at lower angles, where radiation patterns have been optimized to suppress signals at extremely small or negative angles. SNR values are affected by satellite elevation angle in addition to interference. The SNR signal comprises a high amplitude, low-frequency component in SNR direct (SNRD) and a low amplitude, high-frequency component in SNR reflected (SNRR). The design of radiation patterns results in a lower amplitude and clearer appearance of higher frequency signals at low elevation angles. The amplitude of the SNRR is

lower than the noise of the observations at high elevation angles, whereas the multipath effect is visible at low satellite elevations.

2.2 Receivers and their advancement

*2.2.1 Ground-based receivers*

The GNSS-IR technology was distinctly developed in the early 2010s. Initially, geodetic GNSS receivers were employed for applications such as assessing vegetation characteristics and estimating soil moisture [27], [28]. GNSS-IR, however, uses commercial geodetic receivers, hence the majority of the advancements have come from fresh techniques rather than new receivers or technology [29]. Nevertheless, it is important to note that the GNSS-IR paradigm has led to the development of new applications. The GNSS-IR concept was used to monitor sea level [30], multi-frequency observations alongside a four-layer scattering model were also used to retrieve sea ice and snow thicknesses [31], and lake ice thickness was first retrieved [32]. An innovative method of technology that creates an image resembling synthetic aperture radar (SAR) by utilizing the dispersed GNSS-R signals [33]. This system relies on ground-based GNSS-R receivers, which accurately calculate and compensate for the Doppler shift and delay of a satellite's reflected signal as it passes across the sky. An image of a large area can be created by performing a processing procedure similar to SAR [34].

*2.2.2 Airborne receivers*

Airborne GNSS-R receivers have been essential in showcasing new techniques and technologies, with Katzberg and Garrison acquiring the first signal from an airborne platform [35]. Before the CYGNSS constellation was put into operation, there were a lot more GNSS-R sensors in airborne operations. The instruments in this section include those that have seen major technological advancements recently. The GOLD-R instrument, developed by ICE-CSIC/IEEC, UPC, and ESA, was a ground-breaking device that could operate in the GPS L1 band at different polarizations. It has a single-LHCP patch antenna that can sample up to 20 MHz bandwidth and can function in various modes by taking samples of both direct and reflected signals [36], [37]. Another noteworthy instrument is the Global Navigation Satellite System Reflectometry Instrument (GLORI), designed in 2015, which conducts polarimetric measurements using a dual-polarization RHCP/LHCP antenna system [38], [39]. The GLORI has demonstrated the ability to differentiate between RHCP and LHCP signals, making it useful for future spaceborne missions like HydroGNSS [39]. The Microwave Interferometric Reflectometer (MIR), developed between 2015 and 2018, is the initial GNSS-R sensor designed to provide integrated GNSS L1 and L5 readings [40]. According to Ruf et al. [41], the forthcoming generation of GNSS-R equipment can operate in the L1/L5 bands in the GPS and Galileo constellations and was created for airborne platforms. It was implemented by Air New Zealand in the middle of 2021 for continuous operation in domestic aircraft, combining features from the GLORI and MIR instruments [42]. Research centres are developing UAV-based GNSS-R receivers for Earth observation with lower cost and higher resolution, demonstrating the potential of incorporating these receivers into commercial aircraft [43].

*2.2.3 Spaceborne receivers*

The initial capture of a spaceborne GNSS-R signal occurred in 2002 during a Space Shuttle radar imager calibration routine. Subsequently, the UK Disaster Monitoring Constellation-1 mission launched the first GNSS-R receiver into space to validate its potential for ocean study [44]. NASA's Cyclone GNSS (CYGNSS) mission utilized a Delay-Doppler map imager (DDMI) receiver, covering mid-latitudes to showcase the potential of microsatellite constellations with moderate costs for Earth observation [45]. The UK-TDS-1 mission, equipped with an enhanced SSTL GNSS-R receiver (SGR-ReSi) using a zoom transform correlator correlation approach, collected data across ocean, land, and ice regions [46]. In 2019, the China Aerospace Science and Technology Corporation (CASC) launched the BuFeng-1 A/B constellation, mirroring the design of the SSTL SGR-ReSi and the CYGNSS DDMI instruments [47]. Additionally, the China Meteorological Administration (CMA) deployed the FY-3E mission in 2021, offering near-real-time data in a polar orbit with a 3-hour latency [48]. The NanoSat-Lab of the Universitat Politècnica de Catalunya (UPC) made contributions to the creation of spaceborne GNSS-R instruments. Launched in 2016, 3Cat-2 was the first CubeSats mission to introduce the dual-band polarimetric GNSS-R instrument. However, data recovery problems were discovered due to a failure in the satellite bus [49]. With the help of software-defined radio technology, UPC NanoSat-Lab oversaw the 2020

FSSCat mission of ESA, combining an L-band radiometer with a GNSS-R receiver [50], [51]. Spire Global Inc., renowned for CubeSat GNSS radio occultation (GNSS-RO), deployed multiple CubeSats for global GNSS-R measurements [52]. The upcoming HydroGNSS mission will feature SSTL's latest SGR-ReSi variant, enabling multi-constellation, multi-polarization, and multiband GNSS-R measurements [53]. Other space mission proposals, including iGNSS-R receivers, have been developed but have never been implemented or launched [54], [55].

## III. SNOW DEPTH RETRIEVAL

### 3.1 Traditional Snow Depth Retrieval Methods

Traditional snow depth estimation methods rely heavily on field-based techniques. A key strategy is field surveys, which involve human examinations using probing equipment or snow stakes put at several sites throughout snow-covered landscapes. These surveys provide direct and exact depth readings, capturing regional snow accumulation fluctuations. Snow pits, which require physical excavation to examine snowpack qualities such as layering, density, and depth, complement this technique by offering an in-depth awareness of the snowpack's properties at specific spots [56]. Furthermore, snow depth probing technologies, such as inserting snow probes or tubes into the snow until they reach the ground, allow for quick and direct depth assessments [57]. Snow courses, which are predefined routes with specific measurement stations, serve as standardized places for periodic measurements, assisting in monitoring changes in snow depth over time, especially for water resource management purposes. Furthermore, in avalanche-prone areas, the construction of avalanche poles or snow stakes allows for constant monitoring and tracking of snow accumulation and stability changes [58]. While these classic field-based procedures require labour-intensive manual efforts and have limited coverage, they remain critical for providing precise and thorough point-specific snow depth readings across a wide range of terrains.

### 3.2 Snow Depth Retrieval Using Remote Sensing Applications

#### *3.2.1 Active microwave remote sensing*

Active microwave sensing, a method for obtaining Snow Water Equivalent, combines interferometric techniques with Synthetic Aperture Radar (SAR). However, limitations exist with the pass frequency of these satellites, occurring just twice per month, rendering them impractical for certain scenarios [59]. Consideration of terrain geometry is crucial since the accuracy of active microwave measurements relies on correcting the phase of reflected and refracted signals to appear orthogonally incident on the snowpack. Despite satellites' excellent resolution, precision is compromised in mountainous regions due to additional length components [60]. Moreover, vegetation and snow metamorphism can cause an uneven snowpack, which can introduce inaccuracies into active microwave observations. Active SAR has advanced to the point where Ku-band and X-band radiation are used simultaneously. By combining surface and volume scattering effects, this method may reduce inaccuracies brought on by reflections in an uneven snowpack [61].

#### *3.2.2 Passive microwave remote sensing*

Snow Water Equivalent (SWE) has been determined since 1978 through the use of passive microwave techniques. These measurements evaluate soil microwave radiation and estimate SWE by comparing measurements with and without snow [61]. These measurements have a swath width of 25 kilometres, limiting their applicability to regional or hemispheric scales. Moreover, in mountainous terrain, the resolution decreases when translating measurements to distances along slopes [62]. Passive microwave detection is challenged by snow transformation and the presence of water concentration, particularly in alpine and sub-alpine areas where snow is frequently near the melting threshold, leading to significant temperature variations inside the snowpack [63]. These variables fluctuate on an hourly temporal and spatial scale inside the snowpack across tens of meters. To solve these problems, Walker & Goodison [64] suggested a method for measuring liquid water content, and hyperspectral remote sensing can be used to calculate grain size. SWE measures of less than 150 millimetres are usually well suited for passive microwave measurements. When accounting for partially covered cells, the presence of vegetation may affect SWE measurement accuracy by up to 50%. Currently, available techniques combine MODIS readings to determine the amount of vegetation cover [65].

#### *3.2.3 Global Navigation Satellite System (GNSS)*

Larson et al. were the first to showcase the retrieval of snow depth utilizing signal-to-noise ratio (SNR) data from a high-precision GNSS receiver in a standard setup. They established strong correlations between these retrievals and on-site measurements [7]. The majority of the data used in this study were at low elevation angles ranging from 5 to 25 degrees. A 2$^{nd}$ order polynomial was used to remove the direct signal component. To convert GPS multipath data changes into snow depth: 1) by estimating the multipath peak frequency $f$ using a Lomb Scargle Periodogram [66][67][68]; and 2) utilizing a model that correlates $f$ with snow depth across a wide range of snow densities.

According to Larson and Nievinski's method [10]:

$$SNR \propto P_d + P_r + \sqrt{P_d P_r \cos\varphi} \quad (1)$$

where $P_d$ is the direct power, $P_r$ is the reflected power and $\varphi$ is the interference phase. Low elevation angles result in smooth SNR measurements without multipath effects. Nevertheless, at these low satellite elevation angles, multiple oscillations appear in SNR measurements due to the presence of multipath effects or interferences. The initial direct trends $P_d$ and $P_r$ need to be eliminated in GNSS-R. Once these direct trends are removed from equation 1, we can isolate the multipath pattern, which is best expressed in simplified terms as follows

$$SNR = A\cos(2\pi f \sin E + \varphi) \quad (2)$$

where E is the satellite elevation angle; A is the amplitude; and $\varphi$ is the phase. $f$ is the oscillation frequency expressed in hertz, it is not a regular temporal frequency. The GNSS antenna receives signals from numerous locations, although the realistic reflection of GNSS signals is dispersed due to surface roughness and snow layers affecting the GNSS signal. The majority of signal energy comes from signals near the fresnel point, as it has the minimum transmission path of all reflected signals that it has received. A quasi-sinusoidal signal about the sine of the elevation angle oscillates repeatedly in the sequence of multipath SNR measurements [69]. The primary frequency of a series (f) is related to the antenna height (H) concerning the snow-covered ground surface using the sine of the elevation angle as an independent variable.

$$H = \frac{\lambda f}{2} \quad (3)$$

To compute snow depth h, using the method below, where $H_\circ$ is the antenna height in the snow-free scenario, which is known ahead of time:

$$h = H_\circ - H \quad (4)$$

The SNR approaches involve the elimination of the low-frequency components of the time series, which are produced by low-pass filtering or low-order polynomial fitting. The resulting SNR time series has quasi-sinusoidal signals with damping amplitudes at high frequencies. This is known as the detrended SNR series. The major frequency of the detrended SNR series fluctuates with antenna height, allowing us to estimate snow depth based on this variation. However, the effective omission of low-frequency components from the SNR data is a major factor determining the snow depth estimation accuracy of the SNR approach [11].

Subsequently, many researchers used Signal to signal-to-noise ratio (SNR) to study GNSS-IR. To validate GNSS-IR snow depth estimates based on SNR L2 frequency, Gutmann used observation data spanning eight months. These estimates were contrasted with airborne LIDAR scans and manual and laser-ranging snow depth observations. When compared to laser data, the GNSS-IR retrievals during the winter season showed a 10 cm bias and 13 cm RMSE [4]. The L4 approach uses a linear combination of carrier phases to estimate snow depth. Despite the geometry independence of the L4 technique, residual ionospheric delays have the potential to taint the combined time series, increasing the inaccuracies associated with snow depth estimate [70].

Furthermore, when comparing snow depth retrievals to manual measurements, Hefty and Gerhátová's analysis of the Signal-to-Noise Ratio (SNR) data of L1 and L2 signals as well as L4 showed that the consistency was better than 5 cm. Nonetheless, biases as large as 10 cm were noted at specific times [71]. Nievinski developed inverse snow depth estimation models based on GPS SNR observations. GPS estimates were validated with GPS constraints and in situ sampling errors by simulations, which also illustrated trends, fringes, susceptibility to parameter changes, and the possible inaccuracy in reflector height inversion. The study suggested an approach for quality controlling (QC) GPS snow sensing estimations that rely on track clusters and underlined the need to assess presently ignored effects. The usefulness of GPS SNR measurements for snow monitoring is heavily influenced by site conditions, making quality control mandatory for GPS-MR operational use. In unfavourable built-up environments, precipitation and melting accumulation are accurately captured in daily snow depth estimates derived from GNSS data, according to the study [72], [73]. There is a strong correlation between the snow depth data from ultrasonic sensors and the GNSS-derived estimates obtained during four winter seasons. Snow depth variability and diverse observation methods cause minor variations of up to 10 cm. GNSS and ultrasonic snow depths have high agreement, making them suitable for urban building snow sensors. Although they are not as accurate as those relying on L2C signals, the L1 and L2P signals from geodetic antennas can nonetheless yield trustworthy estimations of the depth of snow [74]. Larson and Small assessed the usefulness of SNR L1 data in snow depth studies by analyzing L1 SNR data collected over 5 years from 23 sites and comparing the findings of SNR L2C data and in situ measurements. A correlation of 0.95 and 1 cm mean bias was observed when comparing the SNR L1 and SNR L2C values [9]. An alternate method, unaffected by geometry or ionospheric delays, was put forth by Yu et al. utilizing SNR data from L1, L2, and L5 signals for enhanced snow depth estimation. In comparison to previous investigations, they demonstrated improved findings by establishing a relationship between the change in reflector height and spectral maximum frequency [69]. Later, Zhou et al. presented a method that reduces random errors by combining modelling techniques with SNR data from GPS triple-frequency signals. They showed the accuracy in terms of Root Mean Square Error improvement is over 30%, and the suggested method has a good correlation of 0.95 [75].

Yu et al. introduced a method using dual-frequency GNSS signals' pseudorange and carrier phase to calculate snow depth, which is independent of ionospheric delays and geometric characteristics. This makes GNSS viable, as practically all of them can capture carrier phase and pseudorange data, as well as analyze single-frequency signals. However, the SNR approach may be avoided due to the restricted availability of SNR observables, especially in early GNSS devices and RINEX files. Furthermore, some receivers might fail to receive dual frequency signals or triple frequency signals, making combination methods that were used at that time not relevant [76]. To improve applicability, Li et al. processed just single-frequency signals and came up with a method based on carrier phase and pseudorange measurements from single-frequency GNSS signals [11]. Zhou et al. used dual-frequency and triple-frequency signals with pseudorange measurements to offer two innovative approaches for measuring snow depth, respectively. Their methodology avoids the SNR method's mistake in low-frequency component removal and is less affected by snowstorms, which is probably why their results showed somewhat better performance than the SNR method [77]. All of these techniques rely on carrier phase measurements, even though they all show excellent accuracy in measuring snow depth and reduce mistakes caused by the SNR method's insufficient low-frequency signal reduction. To handle carrier phase observations, cycle slips, and integer ambiguity must be addressed. If cycle slips are not identified or fixed, this could complicate snow depth estimate methods and introduce multipath signature contamination. This can result in inaccurate snow depth estimation, affecting the algorithm's overall performance.

The accuracy of estimating snow depth using SNR relies significantly on the accuracy of the primary frequency calculation derived from the SNR series. This estimation is achieved through spectral analysis methods suitable for irregularly sampled data, for instance, the Lomb Scargle Periodogram method. Bilich's work highlighted that changes in antenna environments lead to considerable variability in SNR data due to multipath effects. The SNR observation series can be distorted by unaccounted multipath signals and receiver noise, which can lead to series peak frequency bias and jeopardize the precision of any measurement [22]. The estimation of antenna height derived from an equation is influenced by assuming that the GNSS signal is reflected by a single snow layer. However, numerous layers of snow can reflect signals, resulting in an overestimation of antenna height and an incorrect estimate of snow depth [69]. Z. Zhang et al. proposed various parameter Multi-Layer Retrieval (MLR) models to analyze snow depth variations and SNR measurements, using the Baseline Estimation and Denoising using Sparsity (BEADS) approach to normalize power into baseline and short-term changes. Their results showed that whereas normalized power showed a negative link with snow depth variations, short-term changes from normalized power consistently coincided with snow depth differences. However, because of environmental conditions, the connection between SNR measures and changes in snow depth was smaller at the start of the snow season [78].

Several researchers have engaged in recent studies involving machine learning (ML) and deep learning (DL) techniques for snow depth retrievals. ML, being data-driven, has the potential to yield more precise outcomes by constructing reliable models based on the relationship between data providing for input and output [79]. In contrast to prior machine learning (ML) studies, which mostly employed reconstructed GNSS signals to analyze or combine airborne and spaceborne data, Wang et al. employed deep learning to retrieve snow depth by augmenting the station density of their data sample. Between 2008 and 2017, 25 GNSS-R stations across Alaska were utilized to investigate snow depth retrieval using deep learning approaches, with on-site data and reference values provided from the PBO H2O ground-based GNSS-R network [80]. Zhan et al. presented a back propagation neural network (BPNN) based approach for retrieving snow depth from available satellite data. While showing notable variations in snow depth retrieval outcomes, their model outperformed earlier techniques in terms of accuracy and dependability, with an RMSE of less than 3 cm and a correlation of 0.94 [81]. Altuntas et al. compared three machine learning classifiers with conventional GNSS-IR techniques using GNSS SNR data over 2 years. They found that training ML algorithms within a range of 0–20 cm of GC values produced superior results. This study demonstrated how ML can be used to estimate a variety of parameters using GNSS-IR, including sea level, vegetation water content, soil moisture, and snow depth accumulation [82]. Hu et al. proposed a universal algorithm applicable to diverse snow scenarios, using SNR arcs for snow depth estimation methods and analyzing ground snow detection feasibility through the SVM method. The results revealed high accuracy in ground state detection and improved initial snow retrieval results, reducing RMSE from 20 to 15 cm, especially in snow-free conditions. This algorithm doesn't rely on prior ground measurements and can learn the topographical environment from historical SNR data, widening its applicability to different snow scenarios [83].

Table 1 provides a thorough overview of the existing body of research on snow depth retrievals using GNSS, consolidating essential studies and their specific findings, and providing a comprehensive insight into the advances made in this area of study.

*Table 1 Notable literature of snow depth retrieval using GNSS.*

| *Sl no.* | *Authors* | *Objectives* | *Results* | *Remarks* |
|---|---|---|---|---|
| 1 | Larson et al., (2009) | GPS SNR data snow depth measurement was introduced. | The geodetic receiver, conventional snow sensors, and field observations have shown excellent agreement in measuring plate boundary deformation. | The use of GPS networks for cryosphere research by global geophysical and geodetic agencies is being explored. |
| 2 | Gutmann et al., (2012) | Snow depth estimates with airborne LIDAR scans, manual and laser-ranging snow depth observations based on SNR L2 frequency. | Showed a bias of 10 cm and a RMSE of 13 cm | More research is needed to understand the GPS's spatial footprint and its impact on terrain, including significant alterations in reflector height, slope, and surface roughness. |
| 3 | Ozeki & Heki, (2012) | Snow depth estimation by L4 introduced and compared with SNR L2P and L2C | A pattern of systematic underestimation of about 10 cm was noted, which is typical for both L4 and SNR methods. | Snow depth estimation uses L4 data, but SNR data yields more accurate results, and even less precise L2P SNR data performs adequately in determining snow depths. Further research into the potential uses of L4 for GPS multipath applications would be insightful. |
| 4 | Nievinski & Larson, (2014a) | Inverse modelling of snow depth estimation has been formulated. | For measured snow depths up to 2.5 meters, the evaluation findings show a significant correlation of 0.98 and an RMSE (Root Mean Square Error) range between 6 and 8 cm. Nonetheless, the height of snow in-situ is typically underestimated by the GPS measurements by 5% to 15%. | Quality control measures are necessary because of the significant impact that the site's characteristics have on the usage of GPS signal-to-noise ratio (SNR) measurements for snow monitoring. Several tests are necessary for an ideal quality control plan, which takes the fit quality, statistical degrees of freedom, peak elevation angle, and reflector height uncertainty into account. To precisely determine reflector height over bare soil, more investigation is required. |
| 5 | Nievinski & Larson, (2014b) | Inverse modelling of snow depth estimation has been validated | | |
| 6 | Hefty & Gerhátová, (2014) | The snow depth estimation method utilizes three independent observations focusing on SNR L1 frequencies, SNR L2 frequencies, and carrier phase linear combination L4. | Manual snow depth sensing and GPS multipath analyses show consistency over 5 cm, with some biases at 10 cm. | GPS antennas in terrain topography near buildings and structures are suitable for analyzing ground signals. The study suggests that analyzing multipath behaviour at fixed GNSS stations and its application in assessing the surroundings around antenna installations can enhance the interpretation of observed geodynamic changes. |
| 7 | Yu et al., (2015) | Snow depth retrieval using a linear combination of L1, L2, | The methodology outperforms the L4 model and is comparable to the SNR method, demonstrating the | The goals of future research will be to achieve constellation diversity gain, use multiple satellite constellations for |

| | | | | |
|---|---|---|---|---|
| | | and L5 GPS frequency signals. | undervaluation of snow depth by the SNR and L4 approaches. | triple-frequency schemes, and improve precision and accuracy. |
| 8 | Vey et al., (2016) | Snow depth calculation by GNSS SNR data and Ultrasonic sensor in a built-up environment. | RMSE of 4.3 cm has been shown among GNSS and ultrasonic snow depths | Snow depth estimates obtained from geodetic antenna signals in L1 and L2P bands are consistent but demonstrate lesser accuracy when compared to estimates derived from L2C signals. In the future, hydrological models may incorporate near-real-time GNSS-based predictions of snow depth. |
| 9 | Larson & Small, (2016) | Development of an algorithm for L1 SNR data snow depth calculation and comparison with L2C data and in situ observations. | The findings revealed a 1 cm mean bias and 0.95 correlation, with a bias of -4cm, comparable to a previous study of the L2C retrieval algorithm. | The algorithm is useful for geodetic networks that lack L2C signal tracking or archive data. However, stricter quality control is needed for the L1 SNR data method. |
| 10 | W. Zhou et al., (2019) | A snow depth measurement method based on the SNR combination of GPS L1, L2, and L5 frequencies. | The suggested approach has a substantial correlation of 0.95 and improvement of more than 30% in terms of RMSE | The study suggests that the new method could aid in tracking snow depths and aid in the creation of multi-system and multi-frequency GNSS reflectometry models. |
| 11 | Yu et al., (2019) | Snow depth measurement methods using dual GNSS receiver systems: dual-frequency combination and single-frequency combination are introduced. | The superposition of peaks affects the accuracy of these methods, with the dual-frequency combination method having a larger effect. While the SNR approach is more accurate in the L2 band, the single-frequency combination method is more accurate in the L1 band. | These methods eliminate geometric distance and ionospheric delay, simplifying data processing. Subsequent research will concentrate on noise mitigation, antenna selection, and snowfall measurement using SWE. |
| 12 | Li et al., (2019) | Snow depth measurement using GNSS single-frequency signals using pseudorange and carrier phase observations | The method is validated using geodetic-grade receivers and shows a 2-6 cm RMSE based on GPS, BDS, and Galileo. | The method is independent of satellite selection and measurement location. Future research should focus on weighting different GNSS constellations and methods. |
| 13 | Wang et al., (2020) | Snow depth estimation based on deep learning approach and GNSS. | The newly introduced deep belief network model demonstrates superior performance by incorporating GNSS estimation, showcasing 0.85 R with 15.40 cm RMSE. | The current spatial resolution of Satellite data is coarse, and further research is needed to enhance spatial resolution and explore other deep-learning models. |
| 14 | Hu et al., (2022) | This study uses machine learning to detect ground truth information before snow depth retrieval, classifying snow-free and snow-covered states and using SNR arcs for snow depth retrieval. | The study shows a 96% accuracy with support vector machines, reducing RMSE from 20 cm to 15 cm. | The algorithm doesn't rely on prior ground measurements and can learn the topographical environment from historical SNR data, widening its applicability to different snow scenarios |

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| 15 | Z. Zhou et al., (2022) | Snow depth retrieval utilizing pseudorange measurements obtained from GNSS signals of both dual and triple frequencies. | RMSE of the proposed methods is less than 3.2 cm | The proposed method, the Triple psuedorange combination, maintains its effectiveness despite geometric distance data and cycle slip issues and avoids ionospheric delays. It outperforms the SNR method and shows slight improvements in snowstorm conditions. |
| 16 | Altuntas et al., (2022) | Snow depth measurement using GNSS SNR data and machine learning classifiers. | Enhance the correlations by as much as 19%, while reducing the RMSE from 15.4 to 4.5 cm. | The research illustrates how machine learning algorithms effectively retrieve snow depth using GNSS, indicating ML's capability to estimate different environmental aspects. Subsequent research will concentrate on employing deep learning methods with concealed layers to achieve similar estimation outcomes. |
| 17 | Zhan et al., (2022) | GNSS-IR SNR retrieving snow depth method using the backpropagation neural network algorithm | The results show an RMSE of 0.0297 m and a mean absolute error of 0.0219 m, with a correlation coefficient of 0.9407 utilizing in-field data obtained through the snow telemetry (SNOTEL) | The method employs the backpropagation algorithm, which takes advantage of the self-learning and self-adaptive capabilities of the backpropagation neural network to maximize the contribution of various satellites. Future investigations should emphasize harnessing data from various systems to achieve greater precision and dependability in retrieving snow depth measurements. |
| 18 | Z. Zhang et al., (2023) | Multi-Layer Retrieval (MLR) models have been introduced, offering distinct parameters designed specifically for estimating variations in snow depth. | The accuracy of the RMSEs dropped from 22.05 to 3.89 and 3.40 cm, respectively, after the MLR models were used. The corrected estimates have strong agreement with meteorological data, displaying deviations in regression slope of under 2% and correlation coefficients surpassing 0.97. | The MLR models showed good accuracy and and appears to be no systemic inaccuracy between the estimates and references. Future research should aim to propose a model with more universal applicability. |

The estimation of snow depth using GNSS Reflectometry (GNSS-R) is a rapidly advancing field that leverages the unique properties of signal reflections to measure and monitor snow cover. The Signal-to-Noise Ratio (SNR) approach, particularly through the analysis of detrended SNR series, has shown significant promise. By filtering out low-frequency components, researchers can extract quasi-sinusoidal signals that vary with antenna height, providing a basis for accurate snow depth estimation. Despite its potential, the SNR method faces challenges related to low-frequency component removal and signal multipath effects, which can impact measurement precision. Quality control remains a critical aspect of GNSS-R snow depth estimation. The accuracy of snow depth estimates is heavily influenced by site conditions, multipath effects, and receiver noise. Research by Nievinski and Larson has highlighted the importance of quality control measures such as track clustering and peak elevation angle analysis to ensure reliable measurements. The development of inverse modelling techniques and the use of advanced spectral analysis methods, like the Lomb-Scargle Periodogram, have contributed to mitigating these issues and enhancing the robustness of snow depth estimates [72], [73].

Recent advances, such as the utilization of dual-frequency and triple-frequency GNSS signals, have demonstrated significant advantages over single-frequency systems. Zhou et al.'s approach, which combines modelling techniques with SNR data from multiple GNSS frequencies, has demonstrated substantial reductions in RMSE and high correlation with in situ measurements [77]. This multi-frequency approach mitigates the effects of ionospheric delays and geometric dependencies, providing more reliable snow depth estimates even in adverse weather conditions. The integration of machine learning (ML) and deep learning (DL) techniques with GNSS-R data has further enhanced snow depth retrieval accuracy. Studies by Wang et al., Zhan et al., and Altuntas et al. have demonstrated the efficacy of these approaches, showing improvements in Root Mean Square Error (RMSE) and correlation coefficients. These methods leverage large datasets and sophisticated algorithms to model the relationship between GNSS signals and snow depth, outperforming traditional SNR-based methods [80], [81], [82]. Overall, the continuous advancements in GNSS-R techniques, coupled with the integration of ML and DL models, are paving the way for more accurate and reliable snow depth estimation. These developments are crucial for enhancing our understanding of snow dynamics, improving hydrological models, and supporting climate studies. As research progresses, the implementation of these methods in operational snow monitoring systems will significantly contribute to environmental monitoring and disaster management.

## IV. CONCLUSION

The review comprehensively examines the potential and challenges of utilizing GNSS-R technology for snow depth retrieval in the diverse and challenging terrains of India. Throughout this research, it has become obvious that GNSS-R shows significant promise as a remote sensing instrument for estimating snow depth, providing a non-intrusive and potentially cost-effective way to check this essential parameter. However, the complexity inherent in India's varied geography, where mountainous regions bring distinct challenges such as signal interference, changing snowfall characteristics, and a lack of comprehensive ground truth data, tempers this promise. To address these issues, specialized algorithmic breakthroughs and thorough validation efforts targeted at India's different landscapes are required. Notably, the examined literature emphasizes the importance of performing lengthy field campaigns to collect precise ground truth data that can be used to evaluate and refine GNSS-R-derived calculations. Snow depth retrieval using GNSS-R technology can be achieved using signal-to-noise ratio (SNR) and carrier phase pseudorange methods.

The SNR method is simpler and more accessible, based on the strength of the received signal relative to background noise. It is cost-effective and accessible, offering estimations based on variations in SNR data. The carrier phase pseudorange method, on the other hand, offers increased precision and accuracy by analyzing carrier phase changes caused by signal reflection off the snow surface. It can mitigate error sources and enhance the reliability of snow depth estimations. However, it often requires more sophisticated equipment and algorithms, making it more complex and expensive. The optimal choice depends on specific application requirements, desired accuracy, environmental conditions, available resources, and the trade-off between complexity and precision. Machine learning and deep learning models can revolutionize snow depth estimation in challenging environments. ML and DL models can process vast amounts of data, extract complex patterns, and create predictive models that adapt to diverse terrains and snow characteristics in India's mountainous regions. The successful implementation of GNSS-R technology for snow depth monitoring in India will revolutionize various sectors, including water resource management, disaster mitigation, and climate change studies. Future research aims to refine algorithms, explore synergies with other remote sensing technologies, and assess socioeconomic implications. This review emphasizes the need for sustained research and innovation to unlock the full potential of GNSS-R technology.

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## AUTHOR CONTRIBUTIONS

HS, AB, VG proposed the research, AK and GS wrote the draft version of the manuscript. AK did review and editing. HS, AB and VG supervised. All the authors polished and approved the final manuscript.

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