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Advances in Image-Based Estimation of Snow Hydrology Parameters: A Systematic Literature Review.

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Abstract

Accurately estimating snow hydrology parameters, including snow coverage mapping and snow depth, plays a significant role in comprehending water resource dynamics, flood forecasting, and environmental management in regions influenced by snow cover. These parameters are critical for hydrological models that simulate snowmelt and runoff, which are essential for predicting water availability and managing water resources in snow-covered areas. Traditional methods for estimating these parameters often rely on manual measurements or simplistic models, which can be inadequate for capturing the complexity of snow-related processes. In recent years, there has been a growing interest in leveraging deep learning techniques for snow hydrology parameter estimation, offering the potential to overcome these limitations. This review paper comprehensively analyzes the current state, challenges, and future directions of image-based approaches in snow hydrology parameter estimation. By harnessing the power of automated methods, particularly deep learning, these approaches demonstrate the ability to capture intricate spatial and temporal relationships present in image data. A comparative analysis between traditional and image-based methods highlights the strengths of automated approaches, including scalability and accuracy. Integration of image sensors, such as satellite imagery and crowd-sourced data, is explored as a crucial component of snow hydrology parameter estimation. Various satellite image sources, including Sentinel 1-2, Landsat, and MODIS, are discussed in terms of their suitability for snow hydrological applications. Despite the promise of image-based approaches, challenges remain, including data availability, model interpretability, and transferability. The paper identifies future research directions, emphasizing the exploration of novel deep learning architectures and uncertainty quantification techniques to address these challenges. In conclusion, this review underscores the importance of image-based approaches for advancing snow hydrology parameter estimation. By addressing challenges and maximizing potential impact, these approaches have the potential to revolutionize snow hydrological modeling and environmental management.

Keywords: ***Snow Cover Mapping, Fractional Snow Cover, Snow Extent, Hydrology Model, Machine Learning, Deep Learning, Crowdsourced Data, Image Sensors***

I. Introduction

Remote sensing has become increasingly popular over the last decade, particularly after NASA's Landsat satellites adopted an open data policy in 2008. The Copernicus program by ESA has further increased the accessibility of satellite data by providing free, high-resolution optical and radar imagery of the Earth's surface, as well as chemical composition measurements of the troposphere. These data are expected to be used in conjunction with advanced data analytics tools to promote innovation and economic growth. The Copernicus program aims to make remote sensing as ubiquitous as GPS technology is today, making it accessible to the general population. The expense of using satellite data has also been lowered by various factors like the improved Internet bandwidth, storage capacity, processing power, and the development of sophisticated open source software tools (1).

Accurate and efficient management of water resources is crucial in ensuring sustainable development and mitigating the risks associated with water-related hazards. In this regard, hydrology parameter estimation plays a vital role by providing critical information on snow cover, snow depth, water availability, snow melting, and water body management. Accurate parameter estimation is essential in developing effective water management strategies, such as flood forecasting, drought management, and water allocation planning. Therefore, there is a significant need to focus on reliable and precise hydrology parameter estimation to ensure optimal utilization and conservation of water resources (2).

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Snow hydrology parameter estimation is a crucial aspect of snow hydrology, which is concerned with the study of snow behavior in the hydrological cycle. Estimating hydrological parameters such as snow depth, snow water equivalent (SWE), and snow coverage mapping is crucial for understanding the water balance in snow-covered regions. Over the years, various techniques have been developed for estimating these parameters. Before the introduction of automated methods that utilize machine learning, there existed a manual approach for estimating or measuring the depth of snow. These traditional methods were time-consuming and prone to errors, which led to inaccurate results. However, with the advent of machine learning, it has become possible to estimate these parameters accurately and efficiently, thereby saving time and resources. Wang (3) highlighted the importance of accounting for atmospheric absorption in microwave radiometric measurements for accurate snow depth estimation. Aerial Frequency-Modulated Continuous Wave radar (FMCW) radar, ground-penetrating radar (GPR), and repeat-pass interferometric SAR have all been used successfully to estimate snow depth. (4) found that FMCW radar can accurately measure snow depth in rugged terrain, and (5) demonstrated the correlation between GPR and manual measurements. (6) proposed a method for snow depth estimation using interferometric synthetic aperture radar (SAR), with a focus on the Tianshan Mountains. These studies collectively show the potential of various remote sensing techniques for snow depth estimation. There are several manual methods used to measure snow water equivalent (SWE), such as the snow pillow (7), snow scale (7), gamma attenuation sensor (8), and methods relying on capacitance sensor measurements (9). Another method for measuring snow depth involves an outdoor camera that is fixed in position and aimed at a set of stakes with colored reference markers. This algorithm calculates the snow depth along the stakes by utilizing the reference markers to generate a tensor, converting the measurements from pixels to standard units such as millimeters (10).

The utilization of images for machine learning in hydrology has opened new avenues for understanding and managing water resources. Image sensors, ranging from satellite imagery to ground-based cameras and crowdsourced data, offer valuable spatial and temporal data for monitoring hydrological processes. However, extracting meaningful hydrological parameters from image sensor data presents significant challenges due to the complexity of the natural environment and the limitations of traditional estimation techniques (11).

In recent years, deep learning techniques have emerged as powerful tools for analyzing complex data, including image-based hydrological information. Deep learning algorithms, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), have demonstrated remarkable success in various image-processing tasks, including object detection, classification, and segmentation. Leveraging the capabilities of deep learning models holds promise for improving the estimation accuracy of hydrological parameters from image sensor data(12).

Recent studies also have demonstrated the potential of using satellite images and crowd-sourced social media data for estimating hydrology parameters. (13) and (14) both highlight the value of crowd-sourced data in improving flood hazard understanding and flood monitoring, respectively. (15) and (16) discuss the use of remote sensing data, including satellite images, for estimating hydrological parameters such as precipitation, soil moisture, and surface runoff. (16) specifically emphasizes the need for techniques that exploit the opportunities presented by remote sensing data and the potential of using satellite observations to reduce uncertainties in parameter calibration. These studies collectively underscore the potential of integrating satellite images and crowd-sourced social media data in hydrology parameter estimation.

This systematic literature review aims to provide an overview of the current state of research on the application of image-based techniques for estimating hydrology parameters. By synthesizing existing literature, this review seeks to identify key trends, methodologies, challenges, and knowledge gaps in this rapidly evolving field. Through a structured analysis of the literature, this paper aims to inform researchers, practitioners, and policymakers about the potential of image-based approaches in advancing our understanding of hydrological processes and enhancing water resource management strategies.

A. Research Questions

- **RQ1:** What image-based techniques are currently utilized for estimating snow hydrology parameters such as snow depth, and snow coverage mapping, and how do they compare in terms of performance metrics?
- **RQ2:** What are the strengths and limitations of satellite imagery and deep learning techniques in improving snow cover mapping and fractional snow cover estimation, and how do these techniques contribute to enhancing the understanding of snow hydrology processes?

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- **RQ3:** How effective are deep learning techniques in cloud detection and distinguishing between clouds and snow in satellite imagery, and what challenges remain in achieving accurate and reliable results?
- **RQ4:** In what ways can crowd-sourced data, such as social media posts and ground-based camera images, be integrated with satellite imagery to enhance snow hydrology parameter estimation, and what are the implications for improving the spatial and temporal resolution of snow cover mapping?
- **RQ5:** What are the potential synergies and trade-offs between different technological advancements, such as high-resolution imagery and machine learning algorithms, in enhancing snow cover and snow depth estimation, and how can these synergies be leveraged to address existing gaps and challenges in snow hydrology research?

These refined research questions aim to delve deeper into the specific methodologies, strengths, limitations, and potential applications of image-based techniques, satellite imagery, deep learning, and crowd-sourced data in the context of snow cover and snow depth estimation.

B. Problem Definition

The scrutining of previous work in the introduction part of this paper reveals the potential of using satellite imagery, aerial photography, ground-based cameras, and deep learning techniques to address the limitations of traditional methods and improve the accuracy and efficiency of snow depth and snow cover estimation. However, challenges need to be addressed to fully leverage the capabilities of these advanced techniques.

1) Spatial resolution: Many satellite sensors have coarse spatial resolutions (e.g., 1 km or lower), which fail to capture the intricate local snow distribution patterns influenced by topographical features, especially in high alpine regions.
2) Temporal resolution: Infrequent revisit times of satellites (e.g., every few days or weeks) may miss rapidly evolving snow conditions, leading to inaccurate estimates.
3) Cloud cover: Optical satellite imagery is often obstructed by clouds, resulting in data gaps and missing information.
4) Complex terrain: Mountainous regions with varying slopes, aspects, and vegetation cover pose challenges for accurate snow depth estimation from remote sensing data.
5) Lack of ground truth data: There is often a shortage of high-quality, synchronous ground truth data for validating and training machine learning models for snow depth estimation.
6) Vegetation cover: Dense forest canopies can obscure the underlying snow cover, leading to underestimation of snow extent.
7) Shadows and topographic effects: Shadows and varying illumination conditions due to topography can affect the spectral signatures of snow, complicating the mapping process.
8) Sub-pixel mapping: Accurately estimating fractional snow cover within mixed pixels (containing snow and non-snow surfaces) is challenging because satellite sensors often have limited resolution, making it difficult to distinguish between snow-covered and non-snow surfaces within the same pixel.

Key Terms:

- **Snow Cover (SC)**: Snow cover refers to the extent of land covered by snow at a particular point in time. It is typically expressed as a percentage of the total land area within a specific region.
- **Snow Depth (SD)**: Snow depth represents the vertical thickness of the snowpack at a given location. It is measured from the ground surface to the top of the snow layer and is usually expressed in inches or centimeters.
- **Snow Cover Mapping (SCM)**: Snow cover mapping involves the creation of spatially explicit maps that depict the distribution and extent of snow cover over a particular area.
- **Fractional Snow Cover (FSC)**: Fractional snow cover indicates the proportion of the ground surface covered by snow within a specific area, ranging from 0% (no snow) to 100% (full snow coverage). It provides a continuous measure of snow extent, crucial for monitoring changes over time and estimating snow properties like depth and water content.

The rest of the paper is organized as follows: Section II describe the search strategy and criteria used to identify relevant literature, Section III reviews the existing methods, Section IV presents and discuss on the contribution and limitations leading to a set of conclusions in section V.

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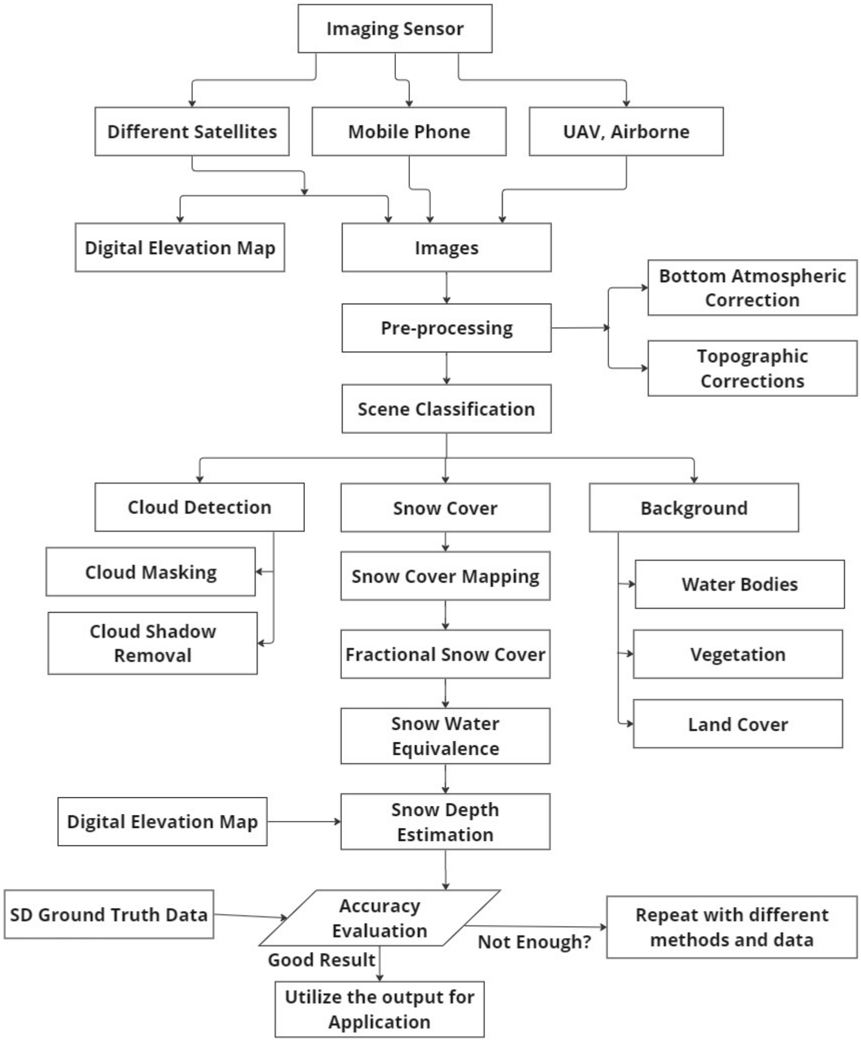

Fig. 1: Basic Steps of Image-Based Snow Hydrology Parameter Estimation

II. Methodology

This study utilized a comprehensive systematic literature review to gain a thorough understanding of the application of Deep Learning in snow hydrology parameter estimation. To ensure thorough coverage of articles, popular academic databases IEEE Xplore, MDPI, Science Direct, Google Scholar, Taylor & Francis Online, and Web of Science were selected for the literature search. Figure 3, which displays the occurrences of major keywords on the implementation of deep learning models in snow hydrology parameter estimation, was generated using VOS viewer software. To account for the dynamic changes in this field, this review mainly considered articles published in the last five years. Comprehensive insights were obtained from former publications, while the latter were used for reports using the tables in this review. To carry out an extensive and thorough systematic review, we limited our research scope to the intersection of remote sensing, deep learning, and hydrology parameter estimation, with a specific emphasis on snow hydrology parameter estimation. This approach ensured that we analyzed the relevant literature comprehensively and accurately, as depicted in Figure 2. Additionally, to conduct a literature search, we created a concept map (Fig3) by using keyword mappings. We combined each word using ”OR” and ”AND”

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conjunctions to search for relevant literature.

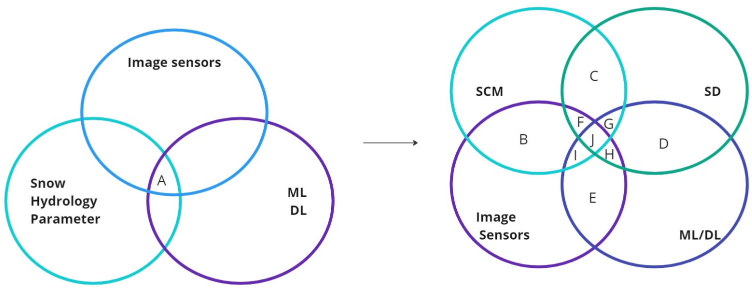

Fig. 2: Scope of the study

III. Systematic Literature Review

The scope of this paper is parameter estimation in snow hydrology, with a focus on snow coverage mapping and snow depth, indicated with an A(left) and I (right) in Figure 2. The figure showcases a combination of different elements in order to achieve a comprehensive solution. A involves the combination of image sensors, hydrology parameter, and machine learning/deep learning. B, on the other hand, merges image sensors with snow cover mapping. C unites snow cover mapping and snow depth estimation, while D links snow depth estimation and ML/deep learning. E connects image sensors and ML/deep learning. F associates snow depth estimation, snow cover mapping, and image sensors. G brings together snow cover mapping, ML/deep learning, and snow depth estimation. H integrates snow depth estimation, ML/deep learning, and image sensors. I relates snow cover mapping, ML/deep learning, and image sensors. Finally, J combines snow cover mapping, image sensors, snow depth estimation, and ML/deep learning.

1. Sources of literature for the literature review

In our analysis, we considered six types of documents: peer-reviewed scientific articles, conference papers, manuals, master thesis, reports, and miscellaneous. We used multiple search engines to gather these documents, with a primary focus on the Web of Science database due to its high standards. However, we also utilized Google Scholar because of its automated full-text search feature and ability to cite references. It was important to critically examine the publication source of the results obtained from Google Scholar due to its automatic nature.

2. Synthesis of literature findings and Case selection criteria

The process of searching for literature was initiated based on several factors including the title, abstract, publisher index, and year of publication. To be specific, the search criteria was based on the conditions outlined in (17), which required that all cases needed to comply with three specific conditions. Firstly, the cases should have been published within the last 6 years 5b. This is to ensure that the information gathered is up-to-date and relevant to current trends and practices in the field of snow hydrology. Secondly, the cases should have used an image-based technique for estimating snow hydrology parameters 5c. This is important because it allows for a more accurate and precise estimation of parameters as compared to other methods. Lastly, the journal of the publisher 5a should have good indexing. This is to ensure that the sources used are from reputable publishers and have undergone a rigorous peer-review process, ensuring that the information presented is of high quality.

A. Satellite and Imagery Sensors

Satellite imagery sensors are critical tools for estimating snow hydrology, providing valuable information on snow cover, depth, and cloud detection. Passive sensors such as radiometers and spectrometers offer detailed data on snow cover extent, albedo, and surface temperature, enabling precise mapping of snow-covered areas. These sensors also assist in snow depth estimation by analyzing the spectral properties of the snow surface. However,

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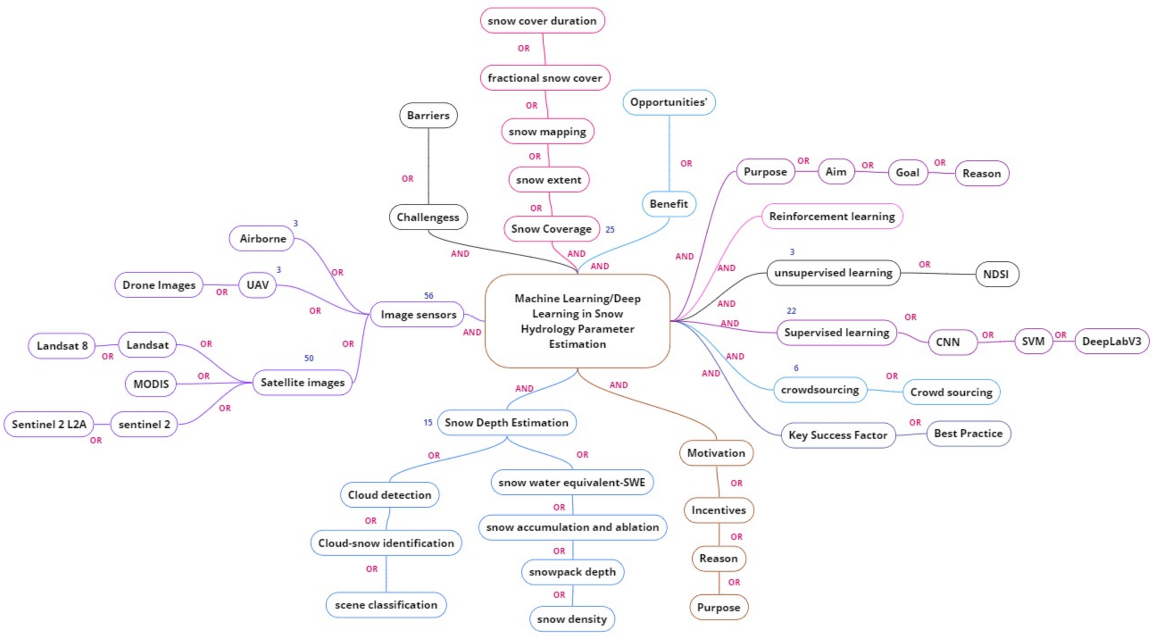

Fig. 3: Keyword used for the literature search. "OR" indicates synonyms, which were incorporated parallel in each search. Topics connected via "AND" indicate different searches. Numbers indicates the total number of studies covered

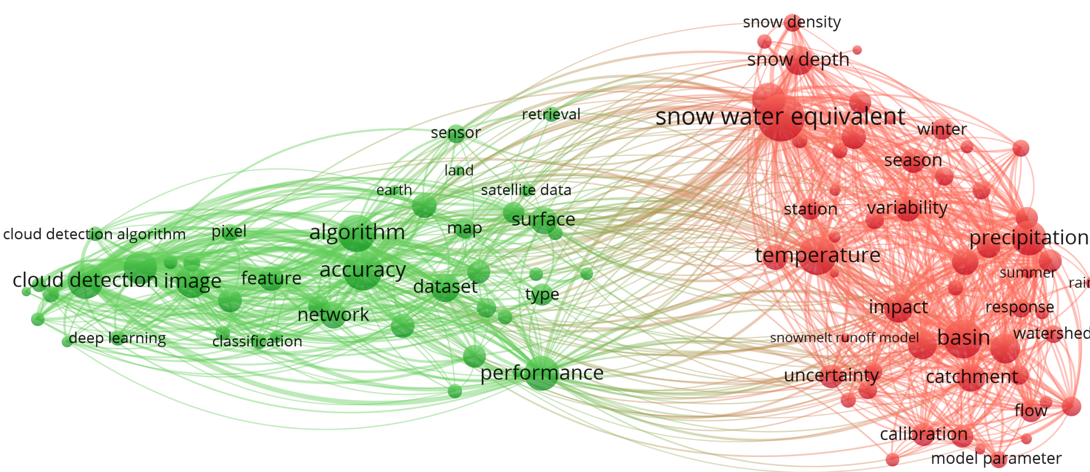

Fig. 4: Reported keyword occurrences in the literature on the implementation of Image-based parameter estimation within the research domain of snow hydrology

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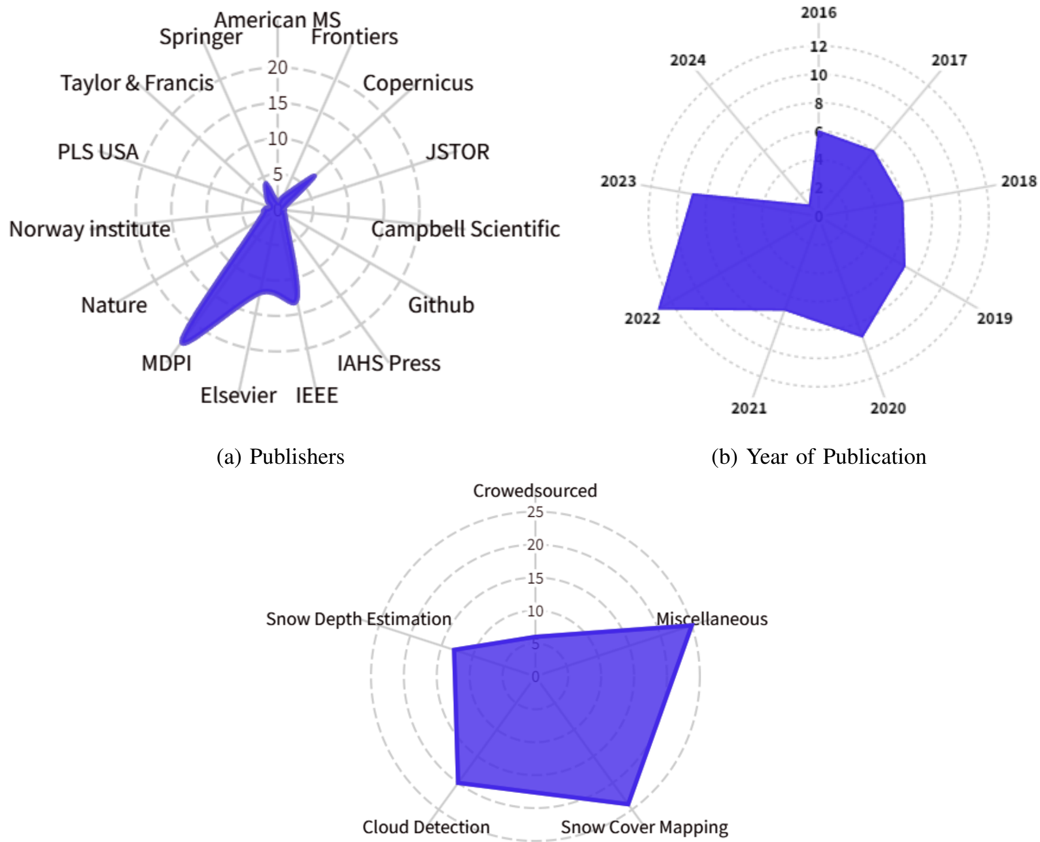

(a) Publishers

(b) Year of Publication

(c) Research Field

Fig. 5: Number of papers covered in this study grouped by publishers, year of publication, and research field. The radar chart indicates the number of papers for each case.

they may have limitations in cloud-covered areas (18). Active sensors such as radar systems and scatterometers can penetrate through clouds, allowing reliable snow depth estimation and cloud detection even in adverse weather conditions. Synthetic Aperture Radar (SAR) technology provides high-resolution imagery that can accurately map snow-covered terrain. Integrating data from both passive and active sensors can enhance our understanding of snow hydrology dynamics, supporting effective water resource management in snow-dominated regions (18). In addition to satellites, there are a variety of airborne sensors that can be used for remote sensing applications. These sensors are capable of producing resolutions that are comparable to those of satellite-based sensors. Their main advantage lies in their ability to cover a wider range of the electromagnetic spectrum and to capture more spectral bands. However, their performance is constrained by their limited range and operational time (19).

Satellite imagery resolution is a critical factor in determining the usefulness and level of detail of the collected data. Different types of resolutions, such as radiometric, spatial, spectral, and temporal, each have unique benefits that must be considered before selecting the appropriate resolution.

- Radiometric resolution is the number of bits used to represent energy in each pixel, which affects the sensor's capacity to distinguish subtle differences.
- Spatial resolution determines the size of each pixel and the area it represents on the Earth's surface, as outlined in table III different satellites has different spatial resolutions.
- Spectral resolution refers to the sensor's ability to differentiate between finer wavelengths, which is essential

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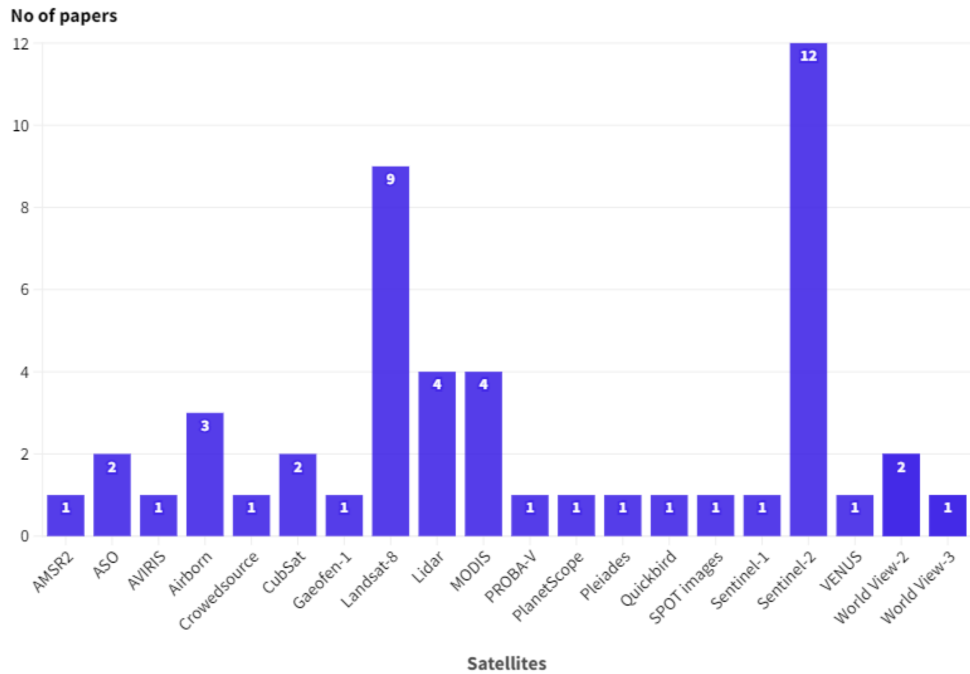

Fig. 6: Number of papers covered in the study grouped by type of satellites

TABLE I: List of satellite/sensor data used in snow cover studies and their related properties (21)

	Imaging Sensors				
	Mono-optical	**Stereo-optical**	**Active optical**	**Passive microwave**	**Active microwave**
	MODIS	SPOT-6/7	ICESat	SSM/I	ALOS-2
	Landsat-8	Pleiades 1a/1b	ICESat-2	SMMR	Sentinel-1
	Sentinel-2/3	WorldView 1-4		AMSR-E	RADARSAT-2
	Meteosat 8-11			AMSU-A/B	TerraSAR-X
	GOES-16-17				
	VIIRS				
	Properties				
Spatial Res	High (10-100 m)	Very High (1 m)	High (10-100 m)	Coarse (km)	Very High (1-20 m)
Temporal Res	High (daily to 5 days)	On request	Very low	High (daily)	High (daily)
Limits	Day/no cloud	Day/no cloud	Revisit time	Coarse res.	Geometrical distortion
Retrieve data	SCF/SCA/Albedo	SD	SD	SD/SWE	SD/Snow wetness
	No direct SWE	No direct SWE		SWE with Tb and Only dry snow	No direct SWE

for recognizing various features.

- Temporal resolution indicates how frequently a satellite revisits the same area, which has an impact on the frequency of observations, as outlined in table II.

Higher resolutions provide more accurate and detailed data for snow hydrology parameter estimation (20). Over the past few years, researchers have been leveraging various satellite image data obtained from multiple sources, as outlined in the chart figure 6. In this review, we aimed to provide an overview of some of the most commonly used satellites and their image sensors. These satellites capture the dynamics of snow cover from a considerable distance above the Earth and differ in their mission objectives, coverage areas, useful lifespan, and technical specifications, as outlined in table I.

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B. Satellite Data Providing Platforms

There are several free satellite imagery data source platforms available, each with unique features and datasets that cater to specific user requirements. USGS Earth Explorer (22) and NASA Earthdata Search (23) offer access to an extensive range of satellite imagery, including renowned datasets like Landsat and MODIS. These platforms provide users with the ability to query, order, and download satellite images for various applications, from environmental monitoring to scientific research. The Sentinel Copernicus Browser (24) is another popular platform that offers high-resolution imagery from the European Space Agency's Sentinel mission, providing global coverage that complements other sources. Sentinel Hub is a cloud-based platform that stands out for its ease of access to Sentinel imagery and other providers' data, along with robust analysis capabilities via an API (25). For advanced users, Google Earth Engine (GEE) (26) is a powerful platform that uses JavaScript for accessing and analyzing satellite imagery. This allows for seamless integration of satellite data into custom scripts for automation and sophisticated geospatial analysis. GEE is a cloud-based service that provides extensive capabilities for remote sensing data analysis. It is built on top of Google Cloud infrastructure and executes computations on Google CPUs and GPUs, making it highly efficient and scalable. The service automates the complexities of parallel computing, allowing users to perform operations in bulk and parallel without having to worry about the technical details. However, it should be noted that GEE has some limitations. The data is stored on private servers, which might not be accessible for certain organizations. Additionally, the image analysis capabilities are limited by the absence of standard preprocessing methods and object-based analysis. GEE has a restricted set of data mining models, which may impact the effectiveness of training samples and input features. Furthermore, GEE is limited to selected data mining models for classification and regression. There are only a few classification and regression algorithms, such as CART, RF, and SVM. Finally, downloading processed data may take some time, and storing complex SAR phase data is not feasible with GEE (27).

Although platforms like Google Earth Engine allow for the analysis of various types of geospatial data, snow extent products are specialized datasets that focus solely on monitoring snow cover. Satellite products are specifically designed for certain applications, offering highly accurate, long-term data with global accessibility. These products are validated for accuracy, provide continuity over time, cover the entire globe, and are freely accessible. While Google Earth Engine (GEE) provides a platform for processing and analyzing geospatial data, satellite products excel in their focus, accuracy, long-term continuity, global coverage, and accessibility. However, satellite products do have limitations such as spatial and temporal resolution, cost and infrastructure requirements, data processing challenges, limited spectral bands, coverage gaps, validation difficulties, and integration issues. These factors can affect their accessibility, accuracy, and usability for certain applications. Nonetheless, satellite products remain invaluable tools for environmental monitoring, research, and decision-making, providing global coverage and long-term data continuity. Table VI lists satellite snow products including snow cover extent and snow water equivalent from the SnowPEx+ ISSPI-3 conference held on February 3, 2021 (28).

C. Type of Satellite Image Data

Upon comprehensive examination of contemporary methodologies for snow cover and snow depth mapping through image-based analysis, it is evident that a variety of input images from different satellite sensors fig 7 are employed. These encompass active microwave, passive microwave, active optical, stereo optical, mono optical, and airborne LiDAR imagery. Active microwave imagery leverages microwave radiation and exhibits the capacity to penetrate through atmospheric obstructions such as clouds and forest cover, rendering it particularly suited for mapping snow cover in regions characterized by limited visibility (29). Conversely, passive microwave imagery measures the microwave radiation emitted by the snow, thereby offering insights into its depth characteristics (30). By utilizing lasers or similar light sources, active optical imagery can create a three-dimensional model of the snow surface, making it easier to estimate snow depth (31; 32; 33; 34). Stereo-optical imagery provides a comprehensive view of the snowscape in three dimensions (34), while mono-optical imagery produces a two-dimensional representation (35). Alternatively, airborne LiDAR technology uses lasers to measure the distance between the airborne platform and the snow surface, providing highly accurate data on snow depth and coverage (36).

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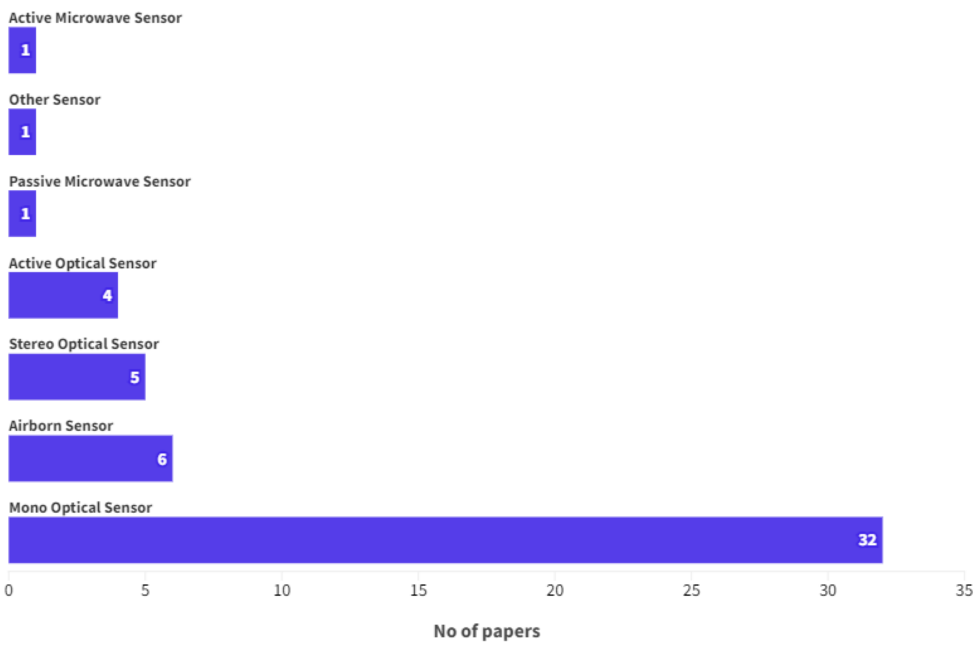

Fig. 7: Number of papers covered in the study grouped by their sensor type used

D. High-Resolution Satellite Imagery Pre-processing

In recent years, there has been a significant development of algorithms for extracting features from high-resolution satellite imagery. However, the classification of these features requires complex algorithms that lack critical refining stages of processing the data at the preliminary phase. Therefore, before extracting semantic data and classifying the features, it is essential to refine the high-resolution imagery. The refinement process involves several interactive steps with the data, which are known as pre-processing algorithms. These pre-processing steps include Geometric correction, radiometric correction, and others. The application of these pre-processing algorithms enhances the accuracy of the data substantially (37). In a recent study by (38), the authors proposed a normalization technique for satellite imagery to improve the accuracy of cloud and cloud shadow detection. Specifically, they normalized the range of values of the image to [0, 1] by maximum normalization or radiation calibration, depending on whether the image can be accurately calibrated.

1) Atmospheric correction is the process of retrieving correct surface reflectance (SR) values from the top of the atmosphere (TOA) radiance values by removing the effect of the atmosphere from the electromagnetic radiation reflected from the earth (39). This involves removing the effects of atmospheric scattering and absorption from the satellite imagery, which can distort the spectral signature of snow. Techniques like dark object subtraction, image-based atmospheric correction, or radiative transfer models are used (40).
2) Geometric correction: This corrects for geometric distortions caused by sensor orientation, terrain relief, and Earth's curvature. Orthorectification using digital elevation models and ground control points is commonly applied to ensure accurate geo-referencing and pixel alignment (41).
3) Radiometric calibration: Raw digital numbers from the satellite sensor are converted to physical units like top-of-atmosphere reflectance or radiance. This enables comparison across different images and scenes (42). Radiometric corrections are necessary for ensuring accurate representation of an input image. These corrections help to identify discrepancies in sensor data and eliminate any unwanted camera sensor defects or atmospheric noise. By perfectly aligning the emitted and reflected radiations with the sensor's calculations, radiometric

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errors can be avoided. Color parameters like brightness and contrast are used to maintain the image's original radiance on the ground (37).

4) Cloud masking: Clouds can have similar spectral properties as snow, leading to misclassification. Cloud masking algorithms use spectral tests, spatial tests, or machine learning techniques to identify and mask out cloud pixels (40).
5) Topographic correction: Illumination effects caused by terrain slope and aspect can distort the spectral signature of snow. Topographic correction algorithms like C-correction or Minnaert correction are applied to compensate for these effects (43).
6) Band ratioing and vegetation indices: Spectral band ratios like the Normalized Difference Snow Index (NDSI) and vegetation indices like the Normalized Difference Vegetation Index (NDVI) are calculated to enhance the contrast between snow and non-snow surfaces.
7) Image fusion: High spatial resolution imagery (e.g., Landsat, SPOT) is fused with high temporal resolution imagery (e.g., MODIS, VIIRS) to combine the advantages of both datasets, improving the accuracy of snow cover mapping.

Landsat sensor-captured images are susceptible to distortion due to various factors such as sensor, solar, atmospheric, and topographic effects. Preprocessing aims to reduce these effects to the degree necessary for a specific purpose. Nevertheless, preprocessing procedures are time-intensive, may not fully eliminate the imperfections, and could potentially introduce more errors (44).

E. Snow Coverage Mapping and Fractional Snow Cover

A range of studies have explored the mapping and prediction of snow coverage. Shi demonstrated a technique using synthetic aperture radar, with coherence measurements proving particularly effective (45). Dickson provided maps of snow-cover probability for the Northern Hemisphere (46), while Haefner emphasized the importance of accurate snow cover mapping for hydrological applications in high mountain regions (47). Gómez-Landesa developed a system for snow cover monitoring in the Spanish Pyrenees, using satellite remote sensing data for snowmelt runoff forecasting. These studies collectively highlight the significance of accurate and timely snow coverage mapping for various applications (48). According to Swamy, the extent of snow cover in the catchment area for each scene has been estimated using supervised classification methodologies such as parallelepiped, nearest neighbor, and maximum likelihood. The study involves the integration of visible and infrared satellite remote sensing data with meteorological and hydrological data obtained from the ground. They investigated the application of a semi-distributed temperature index model in a small, high-altitude catchment area located in the Italian Alps. (49).

Satellite-based snow cover mapping in mountainous regions is a challenging task due to the dynamic landscape structure and wide view of the surface by the satellite. Studies done by (50) demonstrated that strategic image observations with VHR satellites such as WorldView-2 and WorldView-3 can complement the existing operational snow data products to map the evolution of seasonal snow cover. They explored the potential of Maxar WorldView-2 and WorldView-3 in-track stereo images (WV) for land and snow cover mapping at two sites in the Western U.S. with different snow regimes, topographies, vegetation, and underlying geology. Another challenging part of the snow cover mapping based on satellite image is area covred by forests, (32) used lidar-derived snow depth data as ground truth and trained a CNN model with various combinations of input data, including PlanetScope 4-band reflectance products, NDVI, CHM, DEM and its derived attributes. Adding vegetation metrics (NDVI) and DEM-derived metrics (elevation, slope and aspect) to the CNN model improved the accuracy of snow cover mapping, especially in forested areas and canopy edges. The best way to tackle the challenge comes with the land surface is utilizing different satellite combinations, WorldView-2 and WorldView-3 (50), Sentinel-2 and landsat-8 (51), Pleiades, SPOT and Sentinel-2 (34), sentinel-2 and VENUS (52), landsat-8 and MODIS (53). Mapping of snow cover in mountain meadows and forests needs high-resolution satellites, (31) studied the potential of high-resolution satellite imagery for mapping mountain snow cover in forested areas and meadows, with implications for advancing ecohydrological research in a world expecting significant changes in snow. They developed a machine learning model to generate snow-covered area (SCA) maps from PlanetScope imagery at about 3-m spatial resolution. Another high-resolution Cubsat imagery satellite image was utilized to improve the accuracy of snow-covered area mapping at high spatial and temporal resolutions (33). Moreover, getting high-resolution satellite images is not always feasible, and accessing such images may not be open to the public. To address this issue, researchers (54) introduced novel

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method called Multi-Image Super-Resolution (MISR). Instead of relying on a single high-resolution image, MISR leverages multiple low-resolution images of the same scene. The model combines these low-resolution images to create a super-resolved image with enhanced quality. The approach bridges the gap between the demand for high-resolution data and the existing limitations in acquisition capabilities. The proposed model was evaluated using the PROBA-V dataset released by the European Space Agency.

The evaluation demonstrated that the MISR approach performed well, positioning it as a practical solution for real-world remote sensing applications. The model that was developed by (31) achieved a median F1 score of 0.75 for 103 cloud-free images across four different sites in the Western United States and Switzerland. When forest areas were excluded from the evaluation, the model performed even better with an F1 score of 0.82. The model was also tested for accuracy across 7,741 mountain meadows at two study sites in the Sierra Nevada, California, achieving a median F1 score of 0.83. It showed higher accuracy for larger and simpler geometry meadows compared to smaller and more complexly shaped ones. Although SCA mapping in regions close to or under forest canopy remains challenging, the model can identify SCA accurately for relatively large forest gaps (i.e., $15m < DCE < 27m$). The model achieved a median F1 score of 0.87 across the four study sites and showed promising accuracy for areas very close ($> 10m$) to forest edges. In the study conducted by (55), the estimation of fractional snow-covered area, snow grain size, and albedo was successfully achieved using MODIS data. The research showed that the errors in fractional snow cover estimates were minimal, with a pixel-weighted average root mean square (RMS) error of 5% across 31 scenes.

The study conducted by Wang demonstrates the superior performance of both conventional machine-learning and advanced deep-learning methods over the existing rule-based Sen2Cor product for snow mapping (40). They highlighted the effectiveness of the U-Net model with four informative bands (B2, B11, B4, and B9) as inputs. This model was used by collecting and labeling a large dataset for snow coverage mapping, and the methodology involved exploring various input band combinations, comparing reflectance distributions, and training and comparing RF and U-Net models. The results of the study suggest that both conventional machine-learning and advanced deep-learning methods are effective for snow mapping, but the U-Net model with four informative bands as inputs outperforms other methods (40). Researchers explored the optimal selection of image pairs from MODIS and Landsat 8 OLI for fractional snow cover mapping, (53) with a focus on selecting pairs with similar acquisition dates. The study recommends using historical image pairs from the target scene with high similarity, or, if not available, developing an artificial neural network (ANN) using image pairs from another location with the highest similarity in the same acquisition time. Historical image pairs from the target scene with high similarity are the second-best option, while leveraging historical image pairs from another location with high similarity is the third choice. To ensure a comprehensive representation of the study area, the study suggests determining a reasonable location first and then selecting acquisition dates for image pairs. This approach can greatly assist in obtaining accurate and reliable data for fractional snow cover mapping.

In assessing the performance of snow cover mapping algorithms from multispectral satellite data, studies (43) have encountered limitations such as the lack of comprehensive validation data across diverse snow climates and conditions, reliance on empirical NDSI-based methods requiring sensor-specific calibration and thresholding, and computational challenges of spectral-mixture analysis methods for accurate subpixel snow cover estimates (56). Addressing these challenges, this study evaluated and compared seven snow cover products from MODIS, VIIRS, and Landsat 8 sensors utilizing high-spatial-resolution (3 m) snow depth maps derived from airborne lidar data as independent validation data. The evaluated products encompassed two NDSI-based standard products (MOD10A1F and VNP10A1F) and five spectral-mixture products (USGS FSCA, STC-MODSCAG, OLISCAG, and SPIReS MODIS and Landsat 8) (56). This comprehensive validation was conducted across six global seasonal snow classes and various canopy cover fractions, snow cover fractions, and satellite view angles . The assessment employed validation metrics including precision, recall, F-statistic, bias, and RMSE at both pixel and basin scales, providing valuable insights into the performance and reliability of snow cover mapping algorithms across diverse environmental conditions. This study represents a significant advancement in understanding and improving the accuracy of snow cover mapping from multispectral satellite data, with implications for a wide range of applications including hydrological modeling, climate studies, and natural resource management (56). The tables provide a detailed

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TABLE II: Recent Research Developments based on Temporal Resolution

Research Field	Temp Res	Description	Ref
Snow Depth Estimation	daily	Proposed a novel deep residual learning network model (ResSD) to estimate snow depth over the Qinghai-Tibet Plateau (QTP) by combining AMSR2 brightness temperature, MODIS normalized difference snow index, and auxiliary geographic information.	(30)
Snow Depth	daily	The primary objective of this study is to accurately estimate Snow Depth (SD) in Alaska.	(57)
Snow Cover mapping in Mountainous region	daily	An accurate characterization of Snowpack heterogeneity in these ecosystems requires Snow cover observations at high spatial resolutions, yet most existing Snow cover datasets have a coarse resolution.	(31)
Fractional Snow-Cover mapping	daily	They retrieve essential Snow-related information from surface reflectance data acquired by MODIS. fractional Snow-Covered Area, Snow Grain Size, Albedo	(55)
Snow Cover in mountainous regions.	daily	They improved the accuracy of Snow-covered area mapping at high spatial and temporal resolutions.	(33)
Remote sensing for mountain vegetation and Snow cover	1-2 day	They improved high-resolution mapping of Snow-covered areas in complex and forested terrains using PlanetScope imagery and a machine learning approach.	(32)
Snow cover	2 days	They evaluated two methods for mapping the Snow cover area at high spatio-temporal resolution without a shortwave infrared band	(35)
Snow Cover Assessment	2-16 days	They enhanced Snow cover mapping accuracy by combining data from Sentinel-2 and Landsat 8 satellites	(51)
Cloud and Snow Identification	4 days	They studied the feasibility and optimal parameter selection of combining DeepLab v3+ and CRF models for Cloud and Snow identification in GF-1 WFV images	(58)
Fractional Snow cover (FSC) in open terrain	5 days	They estimated the fractional Snow cover (FSC) in open terrain using Sentinel-2 imagery.	(34)
Cloud Detection	5 days	They developed an efficient and accurate Cloud Detection algorithm that works across different satellite sensors and spectral ranges.	(59)
Scene Masking	5 days	They evaluated and compared the performance of different masking algorithms.	(60)
Snow Cover Monitoring	5 days	They accurately map and monitor Snow coverage over a given area.	(40)
Sentinel-2 Image Scene Classification	5 days	They developed a geographically independent Machine Learning (ML) model for Sentinel-2 scene classification with high cross-dataset accuracy.	(61)
Snow Depth Estimation	weekly	They monitored Snow Depth for applications in hydrology, energy planning, ecology, and winter safety evaluation, focusing on high alpine areas where current methods fail to capture local Snow distribution patterns due to topographical features.	(29)
Snow Depth, SWE	weekly	They developed for the measurement of Snow spectral albedo/broadband albedo and Snow Depth/ SWE	(62)
Cloud Detection	16 days	They developed a method for detecting thin Cloud, thick Cloud, and nonCloud pixels in remote sensing images simultaneously. This is crucial for tasks such as Cloud removal and target Detection.	(63)
Cloud Detection	16 days	Developed a fast and accurate method for segmenting cloud in satellite images.	(64)
Cloud Detection	16 days	The paper introduced a Cloud Detection algorithm for satellite imagery based on deep learning, which can improve the accuracy and efficiency of Cloud masking, a critical pre-processing step in optical satellite based remote sensing.	(65)
Cloud Detection	16 days	The paper improved the global Cloud Detection accuracy for Landsat imagery.	(66)
Cloud Detection	16 days	They developed an accurate Cloud Detection algorithm for remote sensing images	(67)

implemented algorithm (Table:IV), along with the evaluation metrics (Table:IV) for spatial (Table:III), temporal (Table:II), spectral, and location (Table:V) aspects.

F. Snow Depth Estimation from satellite images

Monitoring snow depth holds significant importance in various fields, including hydrology, energy planning, ecology, and safety assessment of outdoor winter activities. However, the existing methods for estimating snow depth over extensive areas can only achieve a spatial resolution of up to 1 km of ground sampling distance (GSD). Consequently, these methods are inadequate when it comes to high alpine regions, as they fail to capture the intricate local snow distribution patterns influenced by the prominent topographical features. (29). According to the review conducted by Daudt (29), prior endeavors related to the estimation of snow depth can be classified into two distinct categories. Large-scale estimates, which encompass entire countries or mountain ranges. These estimates are characterized by low spatial resolution. Small-scale estimates, such as 1km, 9km, 25km, and 47km, which offer a higher spatial resolution. Daudt (29) introduced an innovative approach for estimating snow depth on

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TABLE III: Recent Research Developments based on Spatial Resolution

Research Feild	Spatial Res	Description	Ref
Cloud and Snow Detection	0.5-10 meter	They addressed the issues of the low classification accuracy and poor generalization effect by the traditional threshold method, as well as the problems of the misdetection of overlapping regions, rough segmentation results, and a loss of boundary details in existing algorithms	(68)
Mountain Vegetation, snow cover Mapping	0.7-3 meter	They improved high-resolution mapping of snow-covered areas in complex and forested terrains using PlanetScope imagery and a machine learning approach	(32)
Cloud Detection	2.44-2.88 m	The paper addressed the challenge of cloud detection in remote sensing images,which is crucial for various applications like military target recognition and environmental monitoring	(69)
Mountain Snow Cover Mappinmg	3 meter	They did an accurate characterization of snowpack heterogeneity in these ecosystems requires snow cover observations at high spatial resolutions, yet most existing snow cover datasets have a coarse resolution.	(31)
Snow Cover in mountainous regions.	3 meter	They improved the accuracy of snow-covered area mapping at high spatial and temporal resolutions.	(33)
Snow Cover Mapping	5 meter	Two methods were evaluated for mapping the snow cover area at high spatiotemporal resolution using VENμ S satellite, which does not have a shortwave infrared band.	(35)
Snow Depth Estimation	10 meter	They successfully monitor snow depth for applications in hydrology, energy planning, ecology, and winter safety evaluation, focusing on high alpine areas.	(29)
Snow Cover Assessment	10-15 meter	They enhanced snow cover mapping accuracy by combining data from Sentinel-2 and Landsat 8 satellites	(51)
Clouds, Shadows, and Snow Detection	10-20 meter	They developed a self-trained model for cloud, shadow and snow detection in Sentinel-2 images of snow- and ice-covered regions	(70)
Snow Cover Monitoring	10-60 meter	They accurately mapped and monitored snow coverage over a given area.	(40)
Cloud Detection	10-60 meter	They developed an efficient and accurate cloud detection algorithm that works across different satellite sensors and spectral ranges.	(59)
Satellite Image Scene Masking	10-60 meter	They evaluated and compared the performance of different masking algorithms.	(60)
Cloud Detection	15 -120 m	They improved the global cloud detection accuracy for Landsat imagery.	(66)
Cloud and Snow Identification	16 meter	They studied the feasibility and optimal parameter selection of combining DeepLab v3+ , CRF models for cloud and snow identification in GF-1 WFV	(58)
Fractional Snow Cover (FSC) in open terrain	20 meter	The paper estimated the fractional snow cover (FSC) in open terrain using Sentinel-2 imagery.	(34)
Sentinel-2 Image Scene Classfication	20 meter	They developed a geographically independent Machine Learning (ML) model for Sentinel-2 scene classification with high cross-dataset accuracy.	(61)
Remote sensing of snow properties	20 meters	They described and validated an automated model (MEMSCAG) that retrieves subpixel snow-covered area and effective grain size from AVIRIS data, using multiple endmember spectral mixture analysis and a radiative transfer model	(36)
Cloud Detection	30 meter	Developed a method for detecting thin cloud, thick cloud, and noncloud pixels in remote sensing images simultaneously. This is crucial for tasks such as cloud removal and target detection.	(63)
Cloud Detection	30 meter	Developed a fast and accurate method for segmenting clouds in satellite images, which is an important pre-processing step for many remote sensing applications.	(64)
Cloud Detection	30 meter	Introduced a cloud detection algorithm for satellite imagery based on deep learning, which can improve the accuracy and efficiency of cloud masking, a critical pre-processing step in optical satellite based remote sensing.	(65)
Cloud Detection	30 meter	Developed an accurate cloud detection algorithm for remote sensing images	(67)
Fractional Snow-Cover Mapping	30 meter	They retrieved essential snow-related information from surface reflectance data acquired by MODIS. Fractional Snow-Covered Area,Snow Grain Size, Albedo.	(55)
Mountain Snow and Land Cover Mapping using VHR	30-500 meter	Demonstrated that strategic image observations with VHR satellites such as WorldView-2 and WorldView-3 can complement the existing operational snow data products to map the evolution of seasonal snow cover.	(50)
Snow Depth Estimation and SWE	50 meter	Developed for the measurement of snow spectral albedo/broadband albedo and snow depth/ SWE	(62)
Cloud Detection	60 meter	They compared the performance of different machine learning algorithms, including XGBoost, RF, SVM, and CNN	(71)
Snow and Cloud Classification	60 meters	They developed an efficient and accurate algorithm for snow and cloud classification using satellite multispectral remote sensing images.	(72)
Data Selection for Fractional Snow mapping	250-1500 m	They enhanced the accuracy of fractional snow cover (FSC) mapping using an ANN. Specifically, the researchers investigated how to select optimal image pairs from MODIS and Landsat 8 OLI	(53)
Snow Depth Estimation	556 meter	They proposed a novel deep residual learning network model (ResSD) to estimatesnow depth over the Qinghai-Tibet Plateau (QTP) by combining AMSR2 brightness temperature, MODIS NDSI, and auxiliary geographic information.	(30)
Snow Depth	25 km	They studied to accurately estimate snow depth (SD) in Alaska.	(57)

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a national scale. This method generates highly precise weekly estimates with a spatial density of 10 meters ground sample distance (GSD). It employs a fully convolutional, recurrent neural network that utilizes data exclusively from scalable sources, including multispectral optical satellite images, synthetic aperture radar (SAR) images, and a digital elevation map.

A recent study (57) tackled the problem of accurately estimating snow depth in Alaska, a task that is challenging due to complex terrain, harsh climate, and limited ground based observations. The study proposed a novel approach that utilizes a combination of satellite data and ground based measurements using deep learning techniques. To achieve this, deep belief neural(DBN) networks were trained to learn the relationship between various satellite derived features, such as snow cover extent, surface temperature, and reflectance, and ground based snow depth measurements. By leveraging both sources of data, the DBN model achieved higher accuracy in snow depth estimation compared to traditional methods. This approach is particularly useful in areas where ground based observations are sparse, and the results have significant implications for hydrology, climate modeling, and avalanche forecasting. The proposed methodology for establishing the connection between brightness temperature and snow depth (SD) has the potential to improve our understanding of snow dynamics and enhance prediction models. However, the current estimated SD resolution of $25km25$ km is not detailed enough, which limits its use in modeling and monitoring snow related situations. Therefore, it is necessary to enhance the resolution of the SD data to improve the accuracy of the model. Additionally, the use of only one deep learning model (the DBN model) to establish the connection between brightness temperature and SD is not sufficient. It is worth exploring if other deep learning models can handle this issue more effectively. The study focuses on the challenge of estimating snow depth (SD) using satellite data, specifically the AMSR2 and MODIS sensors. Traditional methods are often limited due to the low spatial resolution of AMSR2 and the point to point prediction approach. To overcome these limitations, the researchers (30) proposed a novel deep learning model that combines convolutional neural networks (CNN) and residual blocks. The model adopts an "area to point" approach, taking into account the spatial heterogeneity within an AMSR2 pixel. The study was conducted on the Qinghai Tibet Plateau (QTP) and achieves a spatial resolution of 0.005 degree for SD estimation during the 2019–2020 snow season. The results of the study demonstrate favorable accuracy metrics when compared to in situ observations, with a root mean square error (RMSE) of 2.000 cm, a mean absolute error (MAE) of 0.656 cm, a mean bias error (MBE) of 0.013 cm, and a coefficient of determination (R^2) of 0.847. It is worth noting that the model's performance varies across different regions. The model exhibits slightly larger errors in medium elevation, medium slope, or grassland areas (RMSE: 2.247 cm, 3.084 cm, and 2.213 cm, respectively). However, it performs exceptionally well in low elevation regions (RMSE: 0.523 cm).

Recent advances in remote sensing techniques have significantly contributed to the mapping of snowpack parameters in various terrains, particularly in mountainous regions. Microwave remote sensing has been a key method employed, with both passive and radar-based approaches utilized for measuring parameters such as snow-covered area (SCA), snow water equivalent (SWE), snow depth (HS), and assessing wet/dry states (73). While passive microwaves rely on natural radiation and offer a relatively low resolution, they face limitations such as susceptibility to interference from liquid water in the snowpack and a threshold for SWE, restricting their effectiveness in deep snowpacks (74). On the other hand, radar imagery, utilizing active microwave radiation, presents higher resolution capabilities and the ability to operate in cloudy conditions (75), yet challenges persist due to snow penetration and oblique satellite views, potentially leaving large areas masked (73). Additionally, radar imagery lacks optimal frequency channels for snowpack monitoring (76). To address these limitations, recent studies have explored alternative methods such as mapping snow depth in open alpine terrain using stereo satellite imagery from sources like Pléiades tri-stereo satellites (77) and unmanned aerial vehicles (UAVs) (78). These efforts have involved various photogrammetric processing techniques and bias correction methods to enhance the accuracy and precision of digital elevation models (DEMs) and resultant snow depth maps (78; 79). Furthermore, comparisons with ground-truth measurements from snow probes have been conducted, alongside assessments of factors including snow height, topography, and land cover, to better understand the influences on residual values and improve the reliability of remote sensing-based snowpack mapping in mountainous environments (78; 79).

In the evaluation of snow depth mapping methodologies in mountainous terrain, studies have aimed to refine

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techniques for increased accuracy. Previous research had limitations in validation methods, with reference data not fully capturing topographic and snow depth variability, compounded by a restricted sampling depth of 3.2 meters (77). Addressing these gaps, a more comprehensive validation approach was undertaken, leveraging data from NASA's Airborne Snow Observatory (ASO) campaigns in the Sierra Nevada, USA (43). ASO's airborne laser scanning (ALS) system, operational since 2012, provides detailed measurements of snow depth, snow water equivalent (SWE), and snow albedo across entire mountain watersheds. This study utilized Pléiades stereo triplets to generate high-resolution digital elevation models (DEMs) and snow depth maps using the Ames Stereo Pipeline. Notably, the evaluation was significantly bolstered by comparing the derived snow depth maps with ASO data, enhancing the accuracy and completeness assessment over 138 km^2 of mountainous terrain . Furthermore, the study delved into the impact of various factors such as the base-to-height ratio of stereo images, stereo algorithm, and cost function on the precision and comprehensiveness of snow depth mapping techniques (43). This approach marks a substantial step forward in refining snow depth mapping methodologies, particularly in challenging mountainous environments, offering promising avenues for future research and application in snowpack monitoring and management.

In a study, researchers (42) utilized Landsat-8 images to analyze changes in snow cover and vegetation. The analysis involved calculating the Normalized Difference Snow Index (NDSI) and Normalized Difference Vegetation Index (NDVI) to determine the normalized index of the difference and changes in snow cover and vegetation for Landsat sensor images. The researcher was able to identify the snow surface in photos without cloud cover using the calculated NDSI and NDVI values. In the next step, the researcher applied the calculated NDSI and NDVI values to estimate the snow-covered fraction (SCF) using a formula presented by (80). The formula involved taking the difference between the maximum and minimum NDSI values for the study area and dividing it by the difference between the maximum and minimum NDVI values for the same area. This approach allowed the researcher to determine the percentage of snow cover within the study area. To calculate snow depth, the researcher used the SCF, NDSI and NDVI values to estimate equivalent snow water in the study area, as described by (42). This approach involved using the SCF to determine the fraction of the study area covered by snow, and then multiplying this fraction by the estimated snow water equivalent to determine the total amount of snow water in the area. The resulting value was then divided by the average snow density to obtain the snow depth.

The tables provide a detailed implemented algorithm (Table:IV), along with the evaluation metrics (Table:IV) for spatial (Table:III), temporal (Table:II), spectral, and location (Table:V) aspects.

G. *Cloud Detection, Scene Identification, Cloud-Snow Detection*

Clouds are condensed water vapor visible in the atmosphere, and satellites have become a crucial tool for countries' economic development, particularly with the advancement of remote sensing technology. There are over 2,500 satellites currently orbiting the Earth, and the remote sensing images they capture are proving increasingly valuable in investigating land water resources, vegetation resources, land resources, and environmental monitoring. However, clouds cover approximately 60% of the Earth's surface on average, which can hinder the inversion of atmospheric and surface parameters and block ground objects. This makes it challenging to use remote sensing images effectively. It's therefore vital to detect clouds accurately in remote sensing images to facilitate their subsequent analysis and interpretation. Distinguishing between clouds and snow is especially difficult because they share similar color and texture features in remote sensing images. Accurate cloud detection is critical to improving the accuracy of remote sensing images.(1). Cloud detection plays a crucial role in the processing of remote sensing images, and it is a necessary step for further analysis and interpretation. However, traditional methods of cloud detection face challenges in accurately identifying clouds and snow due to their similar color and texture features(81). Researchers are applied different type of approaches to detect clouds from satellite image and to classify from snow as well. Models implemented among the main papers includes CNN and Transformer integration module (CTIM)(72), DeepLab v3+ and Conditional Random Field (CRF) (58), CNN with modified U-Net(70), multiscale features-convolutional neural network (MF-CNN)(1).

Cloud detection methods that rely on classifying individual pixels based on their spectral signatures sometimes fail to identify clouds accurately on highly reflective surfaces, such as human-made structures or snow/ice, due to the overlooking of spatial patterns. To address this issue, a recent study (65) proposed the use of a deep learning model called Remote Sensing Network (RS-Net), which is inspired by the U-net architecture. Unlike traditional

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pixel-based methods, RS-Net considers spatial context for improved cloud identification. The study found that RS-Net outperforms existing cloud masking methods, such as Fmask, by achieving state-of-the-art performance on two Landsat 8 datasets, especially in scenarios where it is hard to distinguish between clouds and snowy/icy regions. Moreover, RS-Net can be trained on the output of existing cloud masking methods and produce better results compared to the other methods.

The innovative approach, Multi-Scale Convolutional Feature Fusion (MSCFF), presented by the authors (38), is highly effective in detecting clouds in optical satellite imagery captured by different sensors. It stands out from existing methods, thanks to its ability to combine an encoder-decoder module with trainable convolutional filter banks that extract both local and global context from the image. This is crucial for accurate cloud detection, and the model's spatial awareness capability enables it to identify clouds in challenging scenarios, including bright surface-covered areas. To evaluate the model's performance, the researchers used a diverse set of optical satellite images from sensors such as Landsat, Sentinel, and Gaofen. Remarkably, MSCFF outperforms traditional rule-based methods and existing deep learning models. The versatility of MSCFF makes it a promising solution for cloud detection across different spatial resolutions and sensor types, which is of practical significance. Additionally, the availability of their global high-resolution cloud detection validation dataset contributes significantly to the field. The analysis of various cloud-related techniques is being carried out, including but not limited to cloud segmentation, cloud detection, cloud snow classification, scene identification, and cloud masking approaches. These techniques aim to improve the accuracy and efficiency of cloud-related tasks such as weather forecasting and satellite imagery interpretation. The evaluation of multiple approaches allows for a comprehensive understanding of the strengths and weaknesses of each technique, ultimately aiding in the development of more advanced and effective cloud-related snow hydrology(71; 66; 65; 64; 81; 69; 68; 59; 67; 63; 35; 70). The tables provide a detailed on cloud detection on the implemented algorithm (Table:IV), along with the evaluation metrics (Table:IV) for spatial (Table:III), temporal (Table:II), spectral, and location (Table:V) aspects.

H. The Integration of crowd-sourced Images for Snow Hydrology Parameter Estimation

In addressing the limitations of current automated snow monitoring approaches, recent research proposes a novel method that integrates camera imagery, crowdsourcing, and deep learning techniques. Ground-based measurements are often limited in spatial coverage and require costly equipment and manual labor, while satellite imagery may be expensive and suffer from limited temporal resolution due to cloud cover. Additionally, numerical models rely on complex algorithms and input parameters, introducing uncertainties, and crowdsourcing methods, although explored, often lack scalability and consistency in data quality. The proposed approach in this paper addresses the challenges of snow monitoring at larger scales by leveraging camera imagery, crowdsourcing, and deep learning. This enables accurate and frequent monitoring, ranging from continental to global levels (83). Integration of camera imagery provides high-resolution data with continuous coverage, while crowdsourcing allows for the collection of ground truth data at a large scale, enhancing model accuracy and validation (83). Deep learning techniques enable automated analysis of large datasets, improving the efficiency of snow monitoring (83). Through the use of 133 automated cameras, a total of 184,453 near-surface images were captured daily, which were then subjected to processing techniques involving crowdsourcing to ascertain the presence or absence of snow within each image (83). Deep learning models were trained on these images to predict snow presence or absence in unseen images, showcasing the potential of this integrated approach for high-frequency automated snow monitoring at continental to global scales (83). Snow depth estimation from crowdsourced images like social media is a promising approach (11). Recent developments in remote sensing have shown that satellite-based estimations can accurately estimate snow depth on a global scale (84) (85). However, these methods have limitations in low-land areas with dense forest coverage and shallow snow, which are often found near urban areas (86). In the field of remote sensing, citizen observations can be combined with satellite-based estimations to provide more precise solutions. An innovative neural network model has been developed by utilizing snow-related tweets that were annotated using artificial intelligence techniques. This model aims to enhance the accuracy of remote sensing methods for snow estimation. Furthermore, publicly available User Generated Content (UGC) such as geotagged photos and public webcams in mountainous regions can also be analyzed to estimate snow cover and level with greater precision (86).

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TABLE IV: Evaluation Metrics and Implemented Models

Research Field	Evaluation Metrics	Model	Ref
Snow Cover Mapping	Mean Error (ME), Root Mean Square Error (RMSE), Heidle Skill Score(HSS)	NDSI, SVM	(35)
Fractional Snow Cover (FSC) in open terrain	Root Mean Square Error (RMSE), Confidence Interval (CI)		(34)
Snow and Cloud Classification	Accuracy, Mean IoU score, Model Size	Transformer, CNN	(72)
Snow Depth Estimation	Root Mean square Error (RMSE), Mean absolute Error (MAE), Mean bias Error (MBE), Coefficient of determination (R2)	Deep Residual Learning Network by combining CNN and residual blocks	(30)
Cloud and Snow Identification	Mean Intersection over Union (MIoU), Mean Pixel Accuracy (MPA	Conditional Random Field (CRF) models, DeepLabV3+	(58)
Cloud, Shadows, Snow Detection	multi-class segmentation metric, Mean Intersection over Union (mIoU)	CNN with modified U-Net	(70)
Cloud Detection	Precision, Recall, F-Score, Right Rate, Error Rate, False Alarm Rate, Ratio of Right Rate to Error Rate	Multiscale Features-CNN (MF-CNN)	(63)
Cloud Detection	jacard, Precision, Recall, Specificity, overall Accuracy	Cloud-Net inspired by U-Net	(64)
Cloud Detection	Correlation Coefficient, Mean square Error-MSE, Precision, Recall, Sensitivity, F-1 score	Remote Sensing Network (RS-Net), based on the U-net architecture	(65)
Cloud Detection	Cloud Amount Difference (CAD), Overall Accuracy	CNN-extended version of the U-Net	(66)
Snow Cover Monitoring	Accuracy, Precision, Recall, F1-Score,IoU or Jaccard Index, Kappa Cofficent, Confusion Matrix	Random Forest(RF), U-Net	(40)
Sentinel-2 Image Scene Classification	NDVI, F-1, Recall Refelactance ratio(R), Precision	Decision tree, Random Forest, Extra Tree, CNN, Watershed Segmentation (WS)	(61)
Cloud Detection	Jaccard Index, Precision, Recall, Overall Accuracy	Fully Connected Network(FCN)	(67)
Cloud Detection	Mean Intersection Over Union (MIoU), Kappa Coefficient (Kappa), Overall Accuracy (OA), Producer Accuracy (PA), User Accuracy (UA), F1-score	Residual Learning and 1D-CNN (Res-1D-CNN)	(59)
Scene Masking	Classification Accuracy(CA), Producer's Accuracy(PA), Overall Accuracy(OA)	Fmask, ATCOR, and Sen2Cor	(60)
Cloud and Snow Detection	F-1 Score, Mean Pixel Accuracy (MPA), Pixel Accuracy (PA), Mean Intersection over Union (MIoU)	Multi-level Attention Interaction Network (MAINet)	(68)
Cloud Detection	Precision, Recall	CNN	(69)
Snow Depth Estimation	Correlation Coefficient (R), Mean absolute Error (MAE), Root-Mean-square Error (RMSE)	Deep Belief Network (DBN)	(57)
Cloud Detection	User Accuracy (UA), Producer Accuracy (PA), Overall Accuracy, Kappa coefficient, F1 score	XGBoost, RF, SVM, and CNN	(71)
Supper Resolution Images for DL	Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index (SSIM), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Perceptual Metrics	Recurrent Neural Network (RNN), Convolutional Gated Recurrent Unit (ConvGRU)	(54)
Fractional Snow Mapping	R, RMSE, total snow cover area (Tsca)	ANN	(53)
Review of Deep learning in Remote sensing	Accuracy, Recall, Precision, F1-score	CNN(ResNet, DenseNet, EfficientNet, VGG and InceptionV3), Vision Transformer	(82)
Snow Depth Estimation	Mean absolute Error (MAE), Root Mean squared Error (RMSE), Pearson's correlation coefficient, Mean Error (ME).	Recurrent Convolutional Neural Network	(29)

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TABLE V: State of the Art studies classified by their location and data used

Research Field	Data Used	Location	Ref
Mapping Mountain Snow Cover in forested areas and meadows,	Airborne Snow Observatory (ASO) lidar observations, Digital Elevation Map Planet CubeSat images.	USA, Switzerland	(31)
Mountain Snow , Land Cover Mapping using VHR	WorldView-2 and WorldView-3 images	Western USA	(50)
Snow Water Equivalent-SWE, snow depth	Airborne Snow Observatory (ASO)	California, USA	(62)
Fractional Snow-Cover Mapping	MODIS	The Sierra Nevada, Rocky Mountains, high plains of Colorado, and Himalaya, USA	(55)
Snow-Covered Mapping	The AVIRIS data used from the Jet Propulsion Laboratory (JPL) AVIRIS Data Facility	California, USA	(36)
Mountain Vegetation, Snow Cover Mapping	PlanetScope imagery, and the lidar-derived data products	Gunnison, Colorado, USA and Engadin, Switzerland	(32)
Snow Cover Mapping in mountainous regions.	CubeSat imagery and lidar-derived data products	Sierra Nevada, CA, USA, and Rocky Mountains, CO, USA	(33)
Snow Cover Assessment	Sentinel-2 and Landsat-8 images	Babao River Basin of the Qilian Mountains in China	(51)
Snow Cover Mapping	Sentinel-2 and VENuS images	Pyrenees and the High Atlas, France	(35)
Fractional Snow Cover (FSC) in open terrain	Pleiades, Sentinel-2, SPOT images, time-lapse camera images, lidar scans, and crowd-sourced data	Pyrenees, France	(34)
Snow and Cloud classification	Sentinel 2/2A	Global Samples	(72)
Snow Depth Estimation	AMSR2, brightness temperature (TB), (MODIS), NDSI) Auxiliary geographic info, Meteorological SD Data and Digital Elevation Model Data	Southwest of China	(30)
Snow, Cloud Identification	Wide Field View (WFV) sensor data of China Gaofen-1 (GF-1) images	China	(58)
Clouds, Shadows, Snow Detection	Sentinel-2A and Sentinel-2B images	Global Samples	(70)
Cloud Detection	Landsat 8	China	(63)
Cloud Detection	Landsat 8 Biome and SPARCS datasets	Global Samples	(65)
Cloud Detection	Landsat 8 Biome Cloud Mask Validation and The Sentinel-2 Cloud Mask Catalogue dataset	USA	(66)
Sentinel-2 Image Scene Classfication	Sentinel-2 L1C images	Lisbon (Portugal), Ballyhaunis (Ireland), Sukabumi (Indonesia), Béja (Tunisia)	(61)
Cloud Detection	Landsat -8	not specified	(67)
Cloud Detection	Landsat-8 Operational Land Imagers (OLI), MODIS, 20 Sentinel-2 satellite images	Global Sample	(59)
Satellite Image Scene Masking	Sentinel 2	Global Sample	(60)
Cloud and Snow Detection	CSWV and HRC_WHU dataset	Cordillera Mountains of North America	(68)
Cloud Detection	Landsat 8, AIR-CD dataset	Global Sample	(35)
Cloud Detection	Satellite: Quickbird	Global Sample	(69)
Snow Depth Estimation	Airborne data from National Snow and Ice Data Center, in-situ data from the GHCN, GNSS-R SD product data, MOD44B -VCF, ETOPO1 Global Relief Model	Alaska, USA	(57)
Cloud Detection	Baetens-Hagolle, and WHUS2-CD dataset from Sentinel 2	Global Sample	(71)
Supper Resolution Images	PROBA-V dataset	Global Sample	(54)
Data Selection for Fractional Snow mapping	Landsat 8, MODIS	North Xinjiang, China	(53)
Deep learning in Remote sensing	Recent Literatures	Global Sample	(12)
Review of Deep learning in Remote Sensing	EuroSAT, UCMerced-Land Use, NWPU-RESISC45 datasets	Global Sample	(82)
Snow Depth Estimation	Airborne Photogrammetry, Sentinel 1, Sentinel 2, Digital Elevation Map (DEM)	Switzerland and Liechtenstein	(29)

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Crowdsourced social media data can be used to improve flood forecasting by providing high spatiotemporal resolution data, especially in urban areas (2). This data can complement traditional observations and be assimilated into flood forecasting models to reduce uncertainties (87). The integration of crowdsourced social media data with urban flood modeling enhances the understanding of flood dynamics and improves model performance (88). Viero (89) commented (90) that by georeferencing flood impacts and monitoring hazards and impacts, social media data can contribute to a better classification of flood impacts. Additionally, the use of crowdsourced data, along with hydrogeomorphic floodplain terrain processing, can optimize computational domains and improve rapid flood detection (91). This approach can be particularly useful in ungauged river basins with limited data availability. The emergence of crowdsourced data has led to the development of low-cost sensors that allow citizens to participate in hydrological data collection in a more distributed manner than the conventional static physical sensors. Despite this advantage, crowdsourced data has two main disadvantages: irregular availability and variable accuracy from sensor to sensor. These factors make it difficult to incorporate crowdsourced data into hydrological modelling (90). Deep learning-based snow depth estimation has been explored in several studies. One study proposed a wearable IoT platform that utilized pressure and acoustic sensors along with machine learning models to estimate and classify snow depth classes with an accuracy of 94% (92). Another study introduced a deep residual learning network that combined convolutional neural networks (CNN) and residual blocks to estimate snow depth at high spatial resolution using satellite data and elevation maps (30). A pixel-based method was also developed, which utilized microwave snow emission models and machine learning algorithms to retrieve accurate and nearly real-time snow depth estimates (29). Additionally, the use of differential coherence from synthetic aperture radar (SAR) imagery, along with machine learning algorithms, was proposed to quantify snow depth in Texas during a winter storm (84). These studies demonstrated the potential of deep learning approaches for accurate and efficient snow depth estimation. (11)

In this paper, the authors (11) put forth a compelling strategy to improve snow depth estimation by integrating data from Sentinel-1 satellite imagery with social media content from Twitter. The research is motivated by the crucial role of accurate snow depth estimation for civil protection agencies in areas that experience long cold seasons. The authors also highlight the inadequacies of existing remote sensing methods in estimating snow depth in low-lying regions with minimal snow cover, which are often located near urban areas where social media data is prevalent. The authors of this study aimed to address some key limitations of the existing satellite-based method for estimating snow depth. One issue is that the technique struggles in low-lying areas with dense forest coverage and shallow snow depths, which are common conditions in urban environments near cities. This limitation is particularly relevant to the study, which focused on the Helsinki region. Another challenge was the availability of satellite data during the winter period analyzed. Specifically, the Sentinel-1A satellite used for this study provided measurements only every 6 days for one area around Helsinki, with slightly higher but still limited temporal frequency in another area. This infrequent temporal sampling made it difficult to accurately capture rapidly evolving snow conditions. Additionally, the Sentinel-1B satellite, which could have provided supplementary data, did not collect measurements in that region during the study period due to a Baltic Sea ice monitoring campaign. To address these limitations, the authors fused the satellite snow depth estimates with more temporally dense social media data from Twitter to improve overall estimation performance. To estimate snow depth, the authors utilize a well-established technique that leverages Sentinel-1 cross-polarization and co-polarization backscatter measurements. They then extract snow-related information from Twitter using natural language processing on tweet text and computer vision on tweet images. This multimodal social media data is combined with the satellite-derived snow depth estimates through a regression model. The study is conducted in the Helsinki region of Finland over a winter period, and the results are validated against in-situ snow depth measurements from four sites. The authors demonstrate that while the satellite-based method alone has limited accuracy for shallow snow, integrating Twitter data through regression leads to a significant reduction in mean squared error against the ground truth of up to 77%. The best performance is achieved by combining both text and image information from tweets.

I. *Some of Implemented ML/DL Models*

In the past few years, advanced techniques using machine learning and deep learning have been employed to analyze snow depth estimation, snow cover mapping, and cloud detection. These methods have shown promising

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results and have the potential for further development and improvement in the field of snowpack analysis. In this section, we will review papers that implement machine learning and deep learning architectures as outlined by table IV.

1) convolutional Gated Recurrent Unit (GRU) (29) : In order to accurately determine the depth of snow, the neural network needs to possess the ability to recognize both spatial and temporal patterns. Recurrent neural networks are specifically designed neural architectures that are capable of processing inputs in specific sequences, particularly in the time dimension. This makes them highly effective in identifying ordered patterns of inputs, making them a suitable choice for estimating snow depth accurately(29). The Convolutional Gated Recurrent Unit (GRU) is a variant of the GRU, a type of Recurrent Neural Network. Initially, it's designed for video data, capturing spatio-temporal features by introducing convolution operations within the GRU. This results in efficient capture of local patterns and reduced computational complexity. It's used in tasks like action recognition and video captioning (93). Figure 8 displays a diagram of the suggested network, accompanied by a comprehensive schematic of a ConvGRU cell. Each time-step involves concatenating the dynamic inputs for that specific date to the static inputs across the color channel, resulting in an "image" with multiple color channels. The proposed system incorporates 12 channels from optical data, 4 channels from SAR data, and 6 channels of static data derived from elevation maps, resulting in a total of 22 channels. To adjust the number of feature channels, the output layer consists of a 1×1 convolution and the appropriate activation.

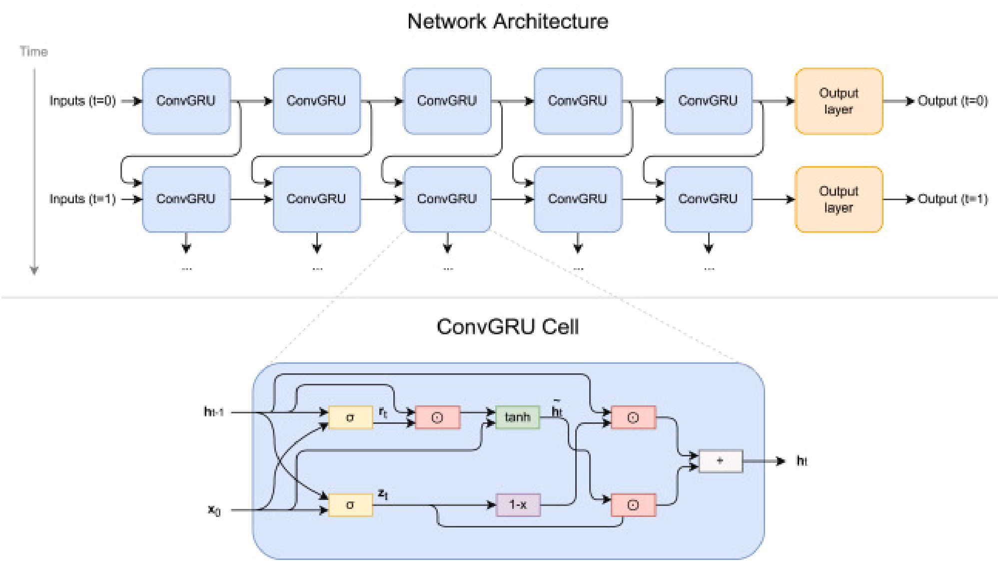

Fig. 8: convolutional Gated Recurrent Unit (GRU) (29), Github implementations (94; 95)

Three sources of input data were utilized, including two dynamic sources that change over time: SAR images from the Sentinel-1 satellites and multispectral optical images from the Sentinel-2 satellites. These sources were selected for their high resolution, frequent revisits, and extensive coverage, and are freely accessible, allowing for the proposed method in this paper to be applied to various regions. Additionally, a static data source, a digital elevation map (DEM), was used to derive and precompute specific features.

2) Deep Belief Network (DBN) (57) : The Deep Belief Network (DBN) model is a multi-layered neural network which consists of a backpropagation (BP) layer along with several restricted Boltzmann machine (RBM) layers. As depicted in Fig. 9, a DBN model with two RBM layers exhibits this structure. In an RBM, the visible layer (v) is utilized to input training data, while the hidden layer (h) extracts data features, with both layers being bidirectionally linked. The first RBM's hidden layer functions as the second RBM's visible layer.

The SSMIS-observed brightness temperature data has been gridded to the EASE-Grid, providing a daily temporal resolution and a spatial resolution of 25 km. The daily datasets contain valuable information such as location, measuring time, and surface density (SD). Additionally, in-situ SD data from 155 sites within the study region

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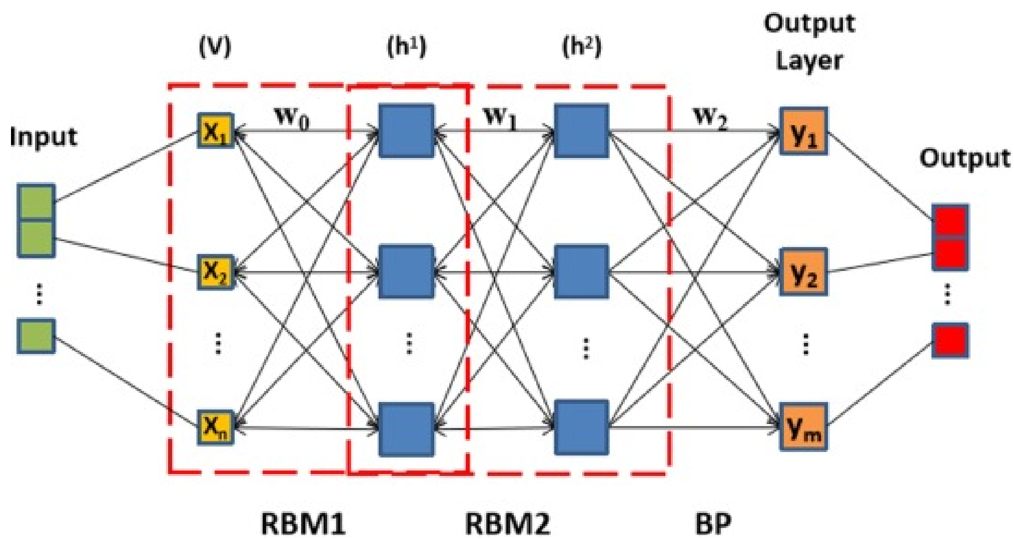

Fig. 9: DBN model structure (57) Github implementation (96)

spanning from 2008 to 2017, along with the daily GNSS-R SD data and Forest cover fraction data, were incorporated to account for the potential impact of forests on SD retrieval. Moreover, the elevation parameter was considered as auxiliary data in order to address the influence of topographic parameters on the accuracy of SD retrieval.

IV. Discussions

Conventional techniques for estimating hydrology parameters, whether manual or automated, have been observed to have limitations in terms of their accuracy and scalability (3). However, deep learning algorithms have shown great potential in addressing these issues by leveraging large volumes of image data for effective learning (29). The use of deep learning methods, particularly neural networks, can provide numerous benefits for estimating snow hydrology parameters based on data collected through image sensors. These techniques are effective at capturing complex spatial and temporal relationships found in image data, and may lead to more accurate and efficient parameter estimation compared to traditional methods. For snow hydrology parameter estimation using crowd-sourced data, convolutional neural networks (CNNs) are often recommended due to their ability to analyze spatial data such as images. CNNs have the advantage of automatically learning relevant features from images, making them an ideal choice for tasks such as snow depth estimation or flood mapping using satellite images or crowd-sourced photos (97; 98).

As demonstrated in the tables (Table: I, II, III, IV, V) presented above, the spatial and temporal resolution of the image utilized for image-based analysis of snow hydrology parameter estimation is of utmost importance in achieving precise results. Particularly in areas with complex landscapes such as alpine regions, mountains, and urban areas, spatial resolution plays a crucial role. Additionally, temporal resolution should be as precise as possible, given the rapidly changing dynamics of snow behavior. Furthermore, satellite selection is a critical factor, as different satellites possess unique properties and revisit times to specific locations. One of the biggest challenges in the field of deep learning for snow hydrology estimation is the task of model training, particularly for supervised learning techniques that require large datasets. However, obtaining labeled snow datasets is not an easy task, especially in the case of snow cover mapping applications. Although satellite images are publicly available, there is a shortage of labeled datasets due to the early stages of deep learning for snow hydrology parameter estimation. As a result, most studies reviewed in this literature review had to create their own data by downloading images from the satellite and performing their own preprocessing steps, such as manual labeling using QGIS tools to train deep learning models, atmospheric correction, and cloud masking. Finally, the model was trained with the labeled data, which is a very time-consuming task.

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TABLE VI: Satellite Snow Products: Snow Cover Extent and Snow Water Equivalent. Adopted from Snowpex (28). The full product name and their website of the satellite product can be found in the appendix section, item 1 to 18.

Product Name	Satellite/Sensor	Snow Parameter	Temporal Res	Spatial Res	Coverage
ParBal	MODIS or VIIRS, MODIS Landsat 8	SWE or melt	daily	463 m	Run on demand; US
GRD SWE Products		SWE	Daily	Variable	Northern Hemisphere (non-mountain)
ESA Snow CCI SWE v1.0	Nimbus-7 SMMR, DMSP F-series S SM/I, SSMIS	SWE	Daily (monthly)	0.25 degree	Northern Hemisphere (excluding mountains, glaciers, ice sheets)
JAXA	GCOM-W AMSR2	SD and SWE	Daily	12.5 km	Northern and Southern Hemisphere
CryoClim SCE, CryoClim	AVHRR GAC and SMMR+SSM/I	SCE (SCEG)	Daily	5 km	Global (NH + SH maps)
SPIReS	VSWIR, tested w MODIS, Landsat 8 OLI, Sentinel2a,b	FSCG, grain size, dus	Daily, smoothed and interpolated over time.	463 m.	Sierra Nevada California,
MODSCAG	Terra, MODIS	FSC (both FSCV and FSCG)	Daily	463 m	Western United States; Canadian Rockies and Alaska; High Mountain Asia; North Pole; South America
CGLOPS NHEMI SCE	Suomi-NPP VIIRS	FSCG	Daily	0.01 x 0.01 degree	25N to 84N, 180W-180E
VNP10A1	Suomi-NPP, VIIRS	SCE	daily	375 m	Global, daylight
MOD10A1	Terra, MODIS	SCE	daily	500 m	Global, daylight
GMASI	AVHRR (METOP/ NOAA), SSMI/SSMIS DMSP F8â€¦19	SCE	Daily	0.04 x 0.04 degree	Global, spatially continuous (no gaps)
Snow-CCI FSC	MODIS, continued SENTINEL-3 SLSTR	FSCV and FSCG	Daily	0.01 deg. (ca 1 km)	global (without Antarctica)
JASMES SNWCFR	AVHRR onboard TIROS-N, NOAA series, MODIS snwcfr_JXAM5_M5C	SCEV	1-day (1D), 1-week (1W), half-month (HM)	0.05 degree (1D, 1W, HM)	Global
JASMES SNWCFR	AVHRR onboard TIROS-N, NOAA series, MODIS snwcfr_ JXAM5_A5C	SCEV	1-day (1D), 1-week (1W), half-month (HM)	0.05 degree (1D, 1W, HM)	Global
JASMES SNWCFR	MODIS snwcfr_ JXM10	SCEV	1-day (1D), 1-week (1W), half-month (HM)	0.05 degree (1D, 1W, HM)	Global
IMS	Various GOES, Himawari, and Meteosat channels, AVHRR, VIIRS, AMSR, ASCAT, AMSU, SSMI,	SCE	Daily, at 00Z, for N. Hemisphere. Twice daily,18Z and 00Z, for N. America.	24km, 4km, 1km	Northern Hemisphere
NSIDC G10035	Interactive analyst SCE charting	SCE	Weekly	Nominal 24 km	Northern Hemisphere land masses
ERA5 , ERA5-Land , ERA5-Snow	Atmospheric Reanalysis , Land surface Model	SWE and FSC	Hourly, hourly , 6-hourly	31 km , 9 km , 31 km	Global

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TABLE VII: Performance Evaluation Metrics of papers. Root Mean Square Error (RMSE), Mean Error (ME), Heidle Skill Score(HSS), Mean absolute Error (MAE), Mean absolute Bias (MBE), Correlation Coefficient(R2), Mean Pixel Accuracy (MPA), Mean Intersection Over Union (MIoU)

	Metrics	**Performance Evaluation Metrics of the Paper in Percent**							
1	**Recall**	(34), 0.96	(72), 0.94	(70), 0.88	(63), 0.89	(64), 0.84	(66), 0.95	(61), 0.84	(69), 0.98 (69), 0.98
2	**Precision**	(34), 0.95	(72), 0.95	(70), 0.95	(63), 0.9	(64), 0.91	(66), 0.92	(61), 0.84	(67), 0.73 (69), 0.85
3	**Accuracy**	(34), 0.95	(72), 0.95	(64), 0.95	(66), 0.94	(40), 0.93	(67), 0.88	(59), 0.95 (69), 0.93	(68), 0.95 (71), 0.84
4	**F-1**	(34), 0.95	(72)0.94	(70), 0.92	(63), 0.83	(66), 0.941	(61), 0.84	(68), 0.94	(69), 0.91
5	**Jacard**	(64), 0.78	(67), 0.65						
6	**Specificity**	(64), 0.98							
7	**RMSE**	(35), 0.045	(34), 0.25	(30), 2.725cm	(57), 15.4cm	(29), 0.91			
8	**ME**	(35), 0.18	(34), -0.05	(29), 0.08					
9	**HSS**	(35), 0.77							
10	**MIOU**	(72), 0.9	(58), 0.816	(70), 0.85	(59), 0.77	(68), 0.90	(69), 0.84		
11	**MAE**	(30), 0.880cm	(57), 9.55cm						
12	**MBE**	(30), -0.259cm							
13	**R2**	(30), 0.698cm	(57), 0.85						
14	**MPA**	(58), 0.941	(68), 0.95	(29), 0.68					
15	**Kappa Cofficent**	(34), 0.9	(59), 0.8	(71), 0.62					

When it comes to estimating the depth of snow, it can be helpful to use satellite images from Sentinel-2, Landsat-8, and MODIS. These satellites have multiple spectral bands, which can provide valuable data. However, a challenge arises because there is a limited availability of labeled data and the ground station data collection is not synchronized with the satellite's revisit time. Consequently, it becomes difficult to directly utilize snow depth information. To overcome this challenge, the Sentinel-1 satellite is a suitable option. It is equipped with Synthetic Aperture Radar technology, allowing it to penetrate clouds and create a digital elevation map for a specific area before and after the snowfall. Nonetheless, there are a few drawbacks to consider. The images generated by Sentinel-1 only have one spectral band, and radar images are not easily analyzed visually for identifying different colors to manually label the data. Although it's beyond the scope of this literature review, there are potential solutions to tackle this issue. One possibility is to use the Sentinel-1 and Sentinel-2 data that are captured at the same time and location, synchronizing them. By manually labeling the Sentinel-2 image while extracting snow depth data from Sentinel-1, we can obtain both labeled data and the corresponding depth information. Another approach worth exploring is applying transfer learning techniques to segment the radar images from Sentinel-1. While estimating snow depth can be challenging due to limited labeled data and unsynchronized ground station measurements, using Sentinel-1 satellite imagery offers a feasible solution. Through the utilization of Sentinel-1 and Sentinel-2 data synchronously, along with potential manual labeling and transfer learning techniques, we can enhance the accuracy of snow depth estimation. The table VII compiles the performance evaluation metrics from each paper, while the table VIII outlines the preprocessing techniques mentioned in the papers. These techniques have been clearly specified in the respective papers for our reference. The table outlining the research questions addressed in the introduction section is presented in table IX according to their previous order code.

V. Conclusion

In conclusion, this review sheds light on the importance, prospects, challenges and various methodological developments associated with the image-based estimation of snow hydrology parameters. Intuitively, the use of remote sensing technology, such as satellite imagery, aerial photography, and ground-based cameras, offers a promising solution to overcome the limitations of traditional in-situ snow measurement methods. In this context, the study revealed the intertwine of various research areas, such as cloud detection, snow modelling, snow cover mapping, fractional snow mapping, snow depth estimation This review has also highlighted the rich panorama of satellite image platforms and products that can be utilized for estimating snow parameters. This includes the commonly used public satellite platforms, Sentinel-1, Sentinel-2, Landsat, and MODIS, which provide moderate

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TABLE VIII: Image Preprocessing Technique Employed in the Paper

	Research Field	Preprocessing	Algorithms	Ref
1	Snow Cover Mapping	Atmospheric Correction and surface Reflectance Adjustment	NDSI, SVM	(35)
2	Fractional Snow Cover (FSC) in open terrain	Contrast Enhancement		(34)
3	Snow and Cloud Classification	Band Resampling, Bottom Atmospheric Correction	Transformer, CNN	(72)
4	Cloud and Snow Identification	Resizing and Resampling	Conditional Random Field (CRF) models, DeepLabV3+	(58)
5	Cloud, Shadows, Snow Detection	Top Atmospheric Correction	CNN with modified U-Net	(70)
6	Cloud Detection	Atmospheric Correction and resizing	Cloud-Net inspired by U-Net	(64)
7	Cloud Detection	Normalization	Remote Sensing Network (RS-Net), based on the U-net architecture	(65)
8	Cloud Detection	Normalization and Top Atmospheric Corrrection	CNN-extended version of the U-Net	(66)
9	Snow Cover Monitoring	Resizing and Top Atmospheric Correction	Random Forest(RF), U-Net	(40)
10	Sentinel-2 Image Scene Classification	Resampling	Decision tree, Random Forest, Extra Tree, CNN, Watershed Segmentation (WS)	(61)
11	Cloud Detection	Normalization	Fully Connected Network(FCN)	(67)
12	Cloud Detection	Top Atmospheric Correction	Residual Learning and 1D-CNN (Res-1D-CNN)	(59)
13	Snow Depth Estimation	Atmospheric Correction	Deep Belief Network (DBN)	(57)
14	Cloud Detection	Geographical Correction	XGBoost, RF, SVM, and CNN	(71)
15	Snow Depth Estimation	Normalization, Resizing	Recurrent Convolutional Neural Network	(29)

TABLE IX: Summary of Research Questions

RQ	Key Findings, their Challenge and Gaps
RQ1	Image-based techniques for estimating snow hydrology parameters, such as snow depth, snow water equivalent (SWE), and snow coverage mapping, include the use of satellite imagery, aerial photography, ground-based cameras, and deep learning techniques. These techniques have shown promising results in improving the accuracy and efficiency of snow depth and snow cover estimation compared to traditional methods. However, challenges such as spatial and temporal resolution, cloud cover, complex terrain, lack of ground truth data, vegetation cover, shadows, and sub-pixel mapping need to be addressed to fully leverage the capabilities of these advanced techniques
RQ2	Satellite imagery and deep learning techniques contribute to enhancing the understanding of snow hydrology processes by improving snow cover mapping and fractional snow cover estimation. Deep learning models, such as U-Net with informative band combinations, have outperformed traditional rule-based methods for snow cover mapping. Integration of high spatial resolution imagery with high temporal resolution imagery through image fusion can enhance the accuracy of snow cover mapping. However, challenges remain in obtaining large, labeled datasets for training deep learning models effectively and accounting for factors like cloud cover and synchronizing ground truth data with satellite imagery
RQ3	Deep learning techniques, particularly CNNs, have shown potential for accurate and efficient estimation of snow hydrology parameters from image data. However, challenges remain in obtaining large, labeled datasets for training these models effectively and accounting for factors like cloud cover and synchronizing ground truth data with satellite imagery. Deep learning models like RS-Net (based on U-Net architecture) and Multi-Scale Convolutional Feature Fusion (MSCFF) have shown improved cloud detection accuracy, even in challenging scenarios where clouds and snow have similar spectral properties. Integration of spatial context and multi-scale features in deep learning models can enhance cloud detection and differentiation from snow. However, the performance of deep learning models may still be limited in certain scenarios, such as thin cloud cover.
RQ4	Crowd-sourced data, such as social media posts and ground-based camera images, can be integrated with satellite imagery to enhance snow hydrology parameter estimation. This integration can improve the spatial and temporal resolution of snow cover mapping and provide more precise solutions for snow depth estimation in low-land areas with dense forest coverage and shallow snow, which are often found near urban areas. However, challenges remain in developing robust algorithms for effective image fusion and optimal band/data selection, as well as improving the accuracy of snow depth estimation from crowdsourced images like social media
RQ5	Synergies between different technological advancements, such as high-resolution imagery and machine learning algorithms, can enhance snow cover and snow depth estimation. For example, the integration of camera imagery, crowdsourcing, and deep learning enables accurate and frequent monitoring of snow depth and snow cover at larger scales, ranging from continental to global levels. However, challenges remain in addressing issues such as data quality, cloud cover, and synchronizing ground truth data with satellite imagery

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to high spatial resolution and frequent revisit times, making them suitable for various snow hydrological studies. From the data processing pipeline, machine learning and deep learning techniques emerge as the most prominent methodological frameworks for image-based estimation of snow hydrology parameters with a great potential for further improvements in the future. However, the implementation of deep learning-based hydrology parameter estimation poses several challenges, including data availability, model interpretability, and transferability. Some high-resolution satellite products are not open source, and ground truth data for validation and testing of the such deep learning models is often difficult to obtain since such data is frequently monitored by governmental agencies with limited access rights. Access to such data is crucial for improving the accuracy of snow hydrological models. Another major challenge in snow hydrological studies is the synchronization of spatio-temporal observations between the ground truth measurement data and the data that we get from the satellite imagery. This is because there may be discrepancies between the two datasets, which could lead to errors in snow hydrology parameter estimation. Therefore, it is important to ensure that the ground truth data and satellite imagery are synchronized to achieve greater accuracy. Cloud cover is another challenge that directly impacts the accuracy of satellite imagery. This is especially pronounced in countries with long winters, like Finland. While satellite imageries from sentinel-1, Sentinel-2, Landsat, and MODIS are valuable for snow hydrology parameter studies, it is crucial to address the challenges associated with well-labeled datasets for deep learning-based hydrology parameter estimation to achieve greater accuracy and reliability. As future research directions, it is crucial to explore novel deep learning architectures, integrate multi-source image data, build large scale dataset with temporal and spatial resolution, and develop relevant techniques for uncertainty quantification and handling. Besides, the study highlights the complex processes involved in the snow hydrology cycle, which require prudent choice of imagery and appropriate integration of various sources.

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Appendix

- **AIR**, Atmospheric Infrared
- **ALOS**, Advanced Land Observing Satellite
- **ALS**, Airborne Laser Scanning
- **AMSR**, Advanced Microwave Scanning Radiometer
- **AMSU**, Advanced Microwave Sounding Unit
- **ANN**, Artificial Neural Network
- **ASO**, Airborne Snow Observatory
- **ATCOR**, Atmospheric Correction
- **CA**, Cloud Assessment
- **CAD**, Computer-Aided Design
- **CD**, Cloud Detection
- **CI**, Cloud Index
- **CNN**, Convolutional Neural Network
- **CO**, Cloud Observation
- **CRF**, Conditional Random Field
- **CTIM**, Cloud-Top Infrared Model
- **CVF**, Convolutional Variational Framework
- **DBN**, Deep Belief Network
- **DEM**, Digital Elevation Model
- **EOS**, Earth Observing System
- **ESA**, European Space Agency
- **FCN**, Fully Convolutional Network
- **FMCW**, Frequency Modulated Continuous Wave
- **FSC**, Fractional Snow Covered
- **FSCA**, Fractional Snow Covered Area
- **GF**, Ground Truth Field
- **GHCN**, Global Historical Climatology Network
- **GNSS**, Global Navigation Satellite System
- **GOES**, Geostationary Operational Environmental Satellite
- **GOSAT**, Greenhouse Gases Observing Satellite
- **GPR**, Ground Penetrating Radar
- **GPS**, Global Positioning System
- **GSD**, Ground Sample Distance
- **HRC**, High-Resolution Camera
- **HS**, Hyperspectral
- **HSS**, Hyperspectral Sensor
- **IAHS**, International Association of Hydrological Sciences
- **ICIP**, International Conference on Image Processing
- **IEEE**, Institute of Electrical and Electronics Engineers
- **IGARSS**, International Geoscience and Remote Sensing Symposium
- **INSAT**, Indian National Satellite System
- **ISPRS**, International Society for Photogrammetry and Remote Sensing
- **JPL**, Jet Propulsion Laboratory
- **MAE**, Mean Absolute Error
- **MBE**, Mean Bias Error
- **ME**, Mapping Error
- **MEMSCAG**, Multiscale Ensemble Snow Depth Mapping Algorithm
- **MF**, Multifrequency
- **ML**, Machine Learning
- **MODIS**, Moderate Resolution Imaging Spectroradiometer

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- **MODSCAG**, MODIS Snow Covered Area and Grain size
- **MPA**, Multilayer Perceptron Algorithm
- **MSE**, Mean Squared Error
- **NASA**, National Aeronautics and Space Administration
- **NDSI**, Normalized Difference Snow Index
- **NDVI**, Normalized Difference Vegetation Index
- **NOAA**, National Oceanic and Atmospheric Administration
- **NWPU**, North Western Polytechnic University
- **OA**, Overall Accuracy
- **OLI**, Operational Land Imager
- **OLISCAG**, Object-Based Linear Spectral Cloud and Snow-Covered Area Mapping Algorithm
- **OR**, Object Recognition
- **PA**, Pixel-Based Algorithm
- **PSNR**, Peak Signal-to-Noise Ratio
- **QTP**, Qinghai-Tibetan Plateau
- **RADARSAT**, Radar Satellite
- **RF**, Random Forest
- **RMSE**, Root Mean Squared Error
- **RNN**, Recurrent Neural Network
- **RS**, Remote Sensing
- **SAR**, Synthetic Aperture Radar
- **SCA**, Snow-Covered Area
- **SCF**, Snow Cover Fraction
- **SD**, Snow Depth
- **SMMR**, Scanning Multichannel Microwave Radiometer
- **SPARCS**, Snow Probabilistic Analysis and Remote Sensing for Complex Terrain Systems
- **SPOT**, Satellite Pour l'Observation de la Terre
- **SSIM**, Structural Similarity Index Measure
- **SSM**, Snow Surface Model
- **STC**, Snow Transformation Coefficient
- **SVM**, Support Vector Machine
- **SWE**, Snow Water Equivalent
- **SWESWE**, Snow Water Equivalent Snow Water Equivalent
- **TB**, Terabytes
- **UA**, User Accuracy
- **UGC**, User Generated Content
- **USA**, United States of America
- **USGS**, United States Geological Survey
- **VCF**, Vegetation Canopy Fraction
- **VEN**, Vending Enhanced Network
- **VGG**, Visual Geometry Group
- **VHR**, Very High Resolution
- **VIIRS**, Visible Infrared Imaging Radiometer Suite
- **VIRIS**, Visible and Infrared Imaging Spectrometer
- **VOS**, Volumetric Observation System
- **WFV**, Wide Field View
- **WHU**, Wuhan University
- **WS**, Watershed

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Satellite Product Names and Their Website for Access

1) ParBal, Parallel Energy Balance Model , Access, Github
2) Gridded Reanalysis-Driven SWE Products
3) ESA Snow CCI SWE v1.0, Access
4) JAXA Daily Snow Depth Product, Access
5) CryoClim SCE, CryoClim Snow Cover Extent Product
6) SPIReS, Snow Property Inversion from Remote Sensing
7) MODSCAG, MODIS Snow Covered and Grain size (also: TMSCAG, OLISCAG, VIIRSCAG)
8) CGLOPS NHEMI SCE, Northern Hemisphere Snow Cover Extent of Copernicus Global Land Monitoring Service, Access
9) VNP10A1, VIIRS/NPP Snow Cover Daily L3 Global 375m SIN Grid, Version 1, Access
10) MOD10A1, MODIS/Terra Snow Cover Daily L3 Global 500m SIN Grid, Version 6, Access
11) GMASI, Global Multisensor Automated Snow/Ice Maps, Access
12) Snow- CCI FSC 1KM MODIS / SENTINEL-3,Access , Data
13) JASMES SNWCFR, JASMES Snow Cover and Cloudiness Product, Access
14) JASMES SNWCFR, JASMES Snow Cover and Cloudiness Product, Access
15) JASMES SNWCFR, JASMES Snow Cover and Cloudiness Product, Access
16) IMS, Interactive Multisensor Snow and Ice Mapping System, Access
17) NSIDC G10035, Rutgers Northern Hemisphere 24 km Weekly Snow Cover Extent, Sept 1980 onward, Access
18) ERA5 / ERA5-Land / ERA5-Snow , Access

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