A Review of Machine Learning in Snow Water Equivalent Monitoring

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Abstract

In recent years, the scientific community focused on snow dynamics has witnessed a surge in efforts aimed at enhancing Snow Water Equivalent (SWE) monitoring capabilities, largely propelled by the incorporation of Machine Learning (ML) techniques. This comprehensive review delves into the current state of research within this evolving domain, shedding light on the indispensable role of precise SWE predictions in bolstering water resource management strategies and fostering environmental resilience amidst the backdrop of climate variability. By critically examining existing literature, this review underscores the imperative nature of ML-based methodologies in overcoming the inherent limitations of traditional monitoring paradigms. Highlighting the adaptability and promise of various ML algorithms, this paper serves as a cornerstone resource for researchers, practitioners, and policymakers dedicated to advancing SWE estimation practices and, consequently, promoting sustainable water resource management in snow-dominated regions.

1 Introduction

1.1 Definition of SWE

Snow Water Equivalent (SWE) determines how much water is available in snow and snowpacks—a reservoir of freshwater lying dormant in Earth's colder regions. These snowpacks are wherein the physics of phase transitions and the thermodynamics of freezing and thawing govern their existence. These processes commence with the precipitation of water vapor onto cold surfaces, resulting in the formation of snowflakes—a phenomenon fundamentally rooted in the principles of nucleation and crystal growth (Libbrecht, 2005). A**s temperatures fluctuate, snowflakes aggregate and evolve into the snowpack, eventually undergoing metamorphosis through processes like sublimation, vapor diffusion, and sintering** (Sturm et al., 2010).

$$SWE = SD \times \rho$$

where SD indicates snow depth and p is the density (Fig. 1). This interplay of physical transformations influences the volume and timing of runoff in downstream watersheds. Thus, precise measurement and prediction of Snow Water are crucial for optimizing water resource management (Dozier and Painter, 2004), ensuring reliable freshwater supply (Harpold et al., 2017), enhancing flood control strategies (Raleigh et al., 2015), and mitigating the impacts of droughts **(**O'Donnell et al., 2019).

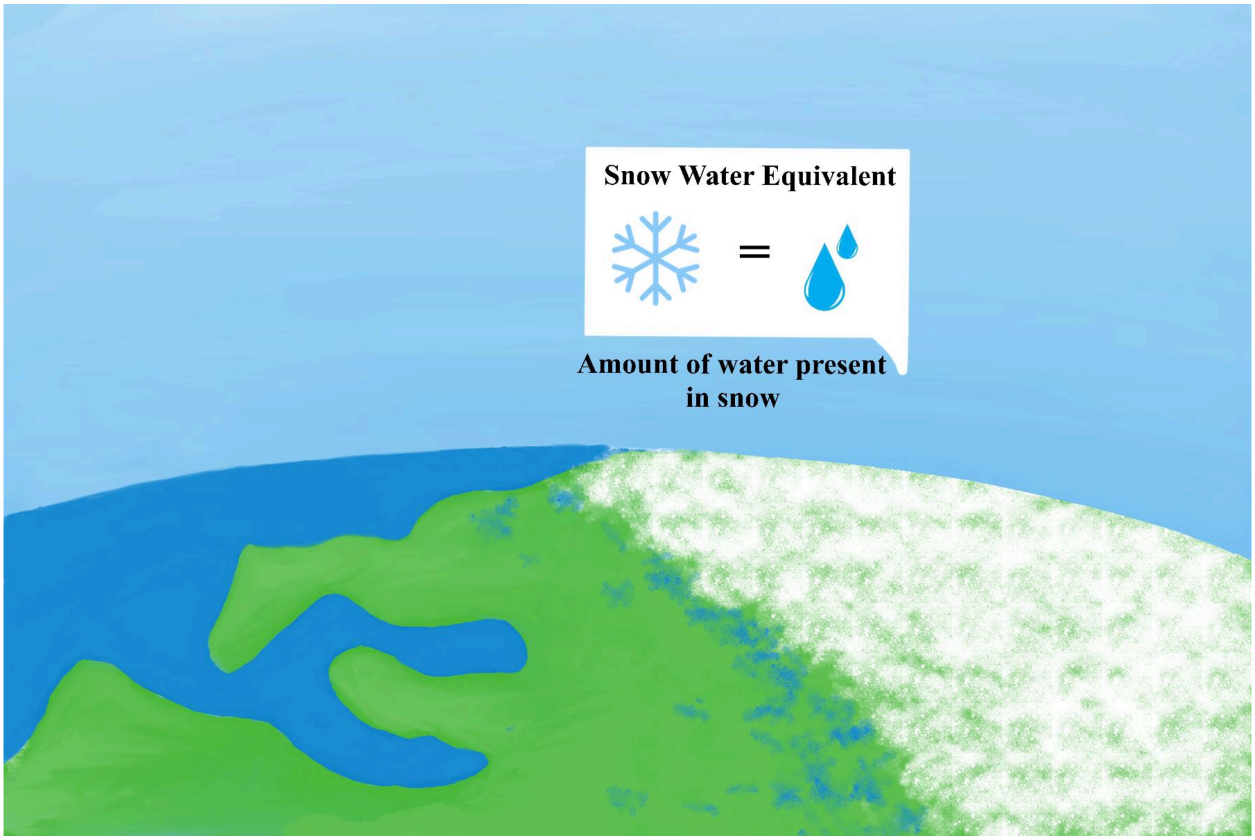

Figure 1. Explanation of SWE

1.2 Significance and Motivation of SWE estimation

Accurate forecasting of SWE is crucial for managing water resources, understanding climate dynamics, and making informed decisions in snow-dominated regions. Historically, SWE estimation has relied on empirical knowledge and physics-based models, which, while valuable, often struggle to capture the complexities of snow processes in a realistic changing climate. To address these limitations and meet the growing demands for precise SWE predictions, the integration of Machine Learning (ML) techniques has emerged as a transformative approach (Broxton et al., 2019) One example ML workflow is displayed in Fig. 2.

The application of ML in SWE estimation is driven by its ability to discern patterns from large and heterogeneous datasets, offering improved predictive accuracy and adaptability to diverse environmental conditions. Furthermore, it can assimilate diverse sources of information, including meteorological data, terrain characteristics, and historical SWE records, to construct predictive models of unparalleled accuracy (Harpold et al., 2017; Raleigh et al., 2015). By harnessing the power of machine learning, we can unveil latent patterns and nonlinear dependencies within SWE datasets, enabling us to make more informed predictions of SWE content and its subsequent implications for water resource management and ecological systems.

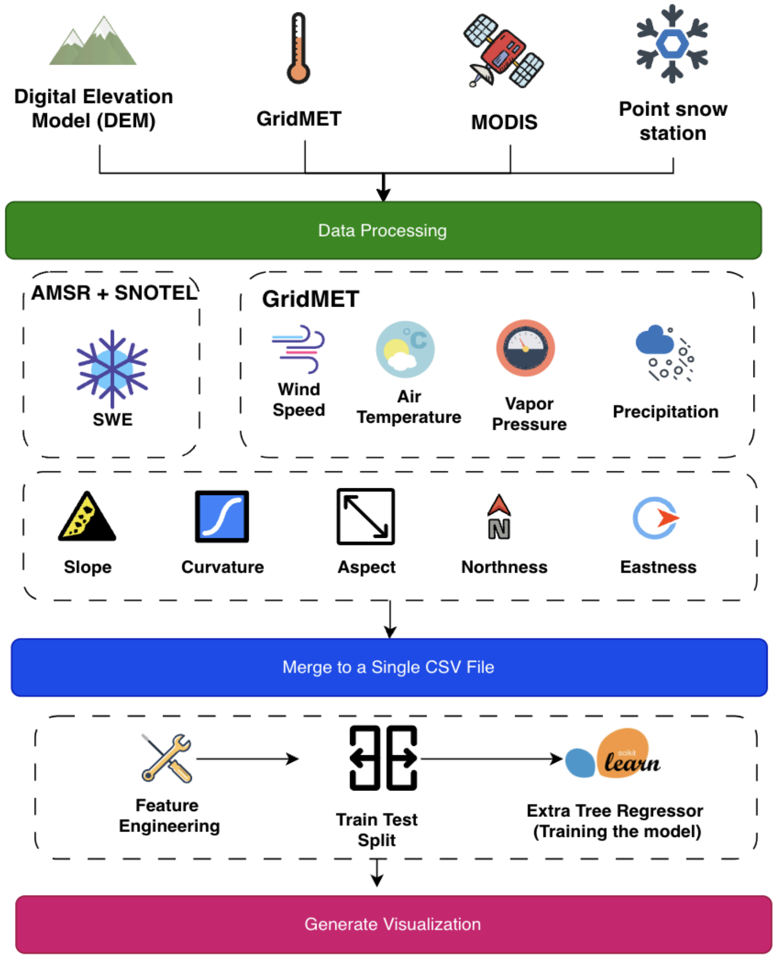

Figure 2. SWE estimation

1.3 Current Operational SWE Monitoring

Monitoring Snow Water Equivalent (SWE) presents significant challenges, leading many facilities to prioritize monitoring and reanalysis efforts. The complex interplay of factors such as terrain, weather patterns, and snowpack dynamics makes accurate forecasting a daunting task. Consequently, the focus has shifted towards operational monitoring and reanalysis systems to provide valuable insights into SWE levels. Despite the absence of widespread SWE estimation operations, several initiatives are dedicated to monitoring and estimating SWE in unmeasured areas. Key among these are the Global Snow Monitoring for Climate Research (GlobSnow) program, the CS725 SWE Sensor developed through collaboration between Hydro Quebec and Campbell Scientific (Canada) Corp, and the Middle Atlantic River Forecast Center (MARFC) operated by the National Weather Service under the United States Department of Commerce.

These systems play a crucial role in providing valuable insights into SWE levels, bridging the gap until more robust monitoring capabilities become available.

1.3.1 Ground Measurements

The accurate measurement of snowpack characteristics is essential for understanding water resource availability and climate dynamics. This section delves into a suite of ground measurement techniques, each contributing distinct insights into Snow Water Equivalent. Snow Pillows are large, flat devices placed on the ground to measure the weight of the snowpack above them. The weight is converted into SWE using established relationships between weight and water content. These sensors are used together with a pressure transducer to measure SWE in SNOTEL/CDEC ground stations. SNOTEL stations are automated monitoring stations that measure various snowpack characteristics, including snow depth and SWE, using sensors and instruments. Data from these stations are transmitted in real-time to a central database for analysis. In tandem with Snow Pillows, the SNOTEL sensor measurements reported daily further enhance our understanding of key environmental parameters. These measurements, with their corresponding sensor types and precision, contribute other insights such as Air Temperature, Barometric Pressure, Precipitation, Relative Humidity, Snow Depth, and most importantly Snow Water Content (Measured using a snow pillow device mentioned above and a pressure transducer, with a precision of 0.1 inches).

Sonic Sensors, also known as ultrasonic sensors, employ sound waves to determine the distance from the sensor to the snow surface. Sonic sensors emit high-frequency sound waves towards the ground surface. These sound waves travel through the air until they encounter an object, such as the snow surface. Upon contact with the surface, the sound waves are reflected back to the sensor. By measuring the time it takes for the sound waves to travel to the surface and back, the sensor can calculate the distance to the surface, which corresponds to the snow depth.

CS725 SWE Sensor (Fig. 3) is a cutting-edge potential snow-pillow replacement, which utilizes a non-contact technology based on the attenuation of gamma radiation emitted by naturally occurring radioactive elements in soil and overburden, particularly Potassium and Thallium. This attenuation varies with water content, allowing for effective SWE measurement. Developed in 2009, the CS725 has undergone extensive field trials in regions including British Columbia, Quebec, Norway, Utah, and New York State. The sensor is mounted pre-snowfall, suspended from a horizontal pipe at a suitable height above the ground to avoid influencing snow accumulation. It measures SWE over a large surface area (50-100m^2) and is compatible with various snow and ice types. Once installed, the CS725 operates maintenance-free in the field for up to seven years. After this period, it requires return to the factory for internal battery replacement and evaluation. The CS725 is presently limited to a maximum range of approximately 600mm of SWE. Site calibration under snow-free conditions is necessary, involving known soil moisture obtained with a soil moisture probe just before ground freeze-up.While satellite-based systems offer extensive coverage, technologies like the CS725 SWE Sensor contribute valuable localized data.

Figure 3. CS725 Measuring SWE in the field (images from CS725 product page)

Snow courses consist of 5-10 sampling points spaced evenly along a transect that can stretch from a few hundred meters to a kilometer. To determine SWE, technicians use a snow tube to measure snow depth at each point, and a snow sampler to collect a core for density analysis. These measurements are then used to calculate SWE. Cosmic-Ray Neutron Sensors are increasingly being used as a novel approach to estimate Snow Water Equivalent (SWE) indirectly. CRNS measures the intensity of subatomic particles known as neutrons that constantly rain down on the Earth's surface from space due to cosmic radiation. These neutrons interact with hydrogen atoms, which are abundant in water molecules, in the soil and snowpack. By analyzing changes in the intensity of these neutrons, researchers can infer variations in soil moisture and snow water content. Manual Snow Surveys involve manual measurements of snow depth and density at multiple locations within a study area. These measurements are used to estimate SWE distribution across the area.

1.3.2 Model Products

ESA's GlobSnow program offers a comprehensive dataset spanning from 1979 to the present, utilizing satellite imagery and ground-based weather station data. It provides valuable insights into SWE across the Northern Hemisphere, excluding glaciers and ice sheets. The SWE estimate is derived from a combination of passive microwave radiometer data and ground-based weather station data, utilizing satellite sensors such as Nimbus-7 SMMR, DMSP (F8/F11/F13) SSM/I, and DMSP F17 SSMIS. Employing a data-assimilation based approach, the product integrates space-borne passive radiometer data at K- and Ka-bands (19 GHz and 37 GHz) with ground-based synoptic weather stations. The SWE maps are generated on a daily, weekly, and monthly basis. The GlobSnow SWE record serves as a reliable resource for monitoring and estimating SWE in non-mountainous regions of the Northern Hemisphere (as shown in Fig. 4). As exemplified by ESA's GlobSnow SWE initiative, current operational applications predominantly focus on monitoring and estimation in areas devoid of direct measurements.

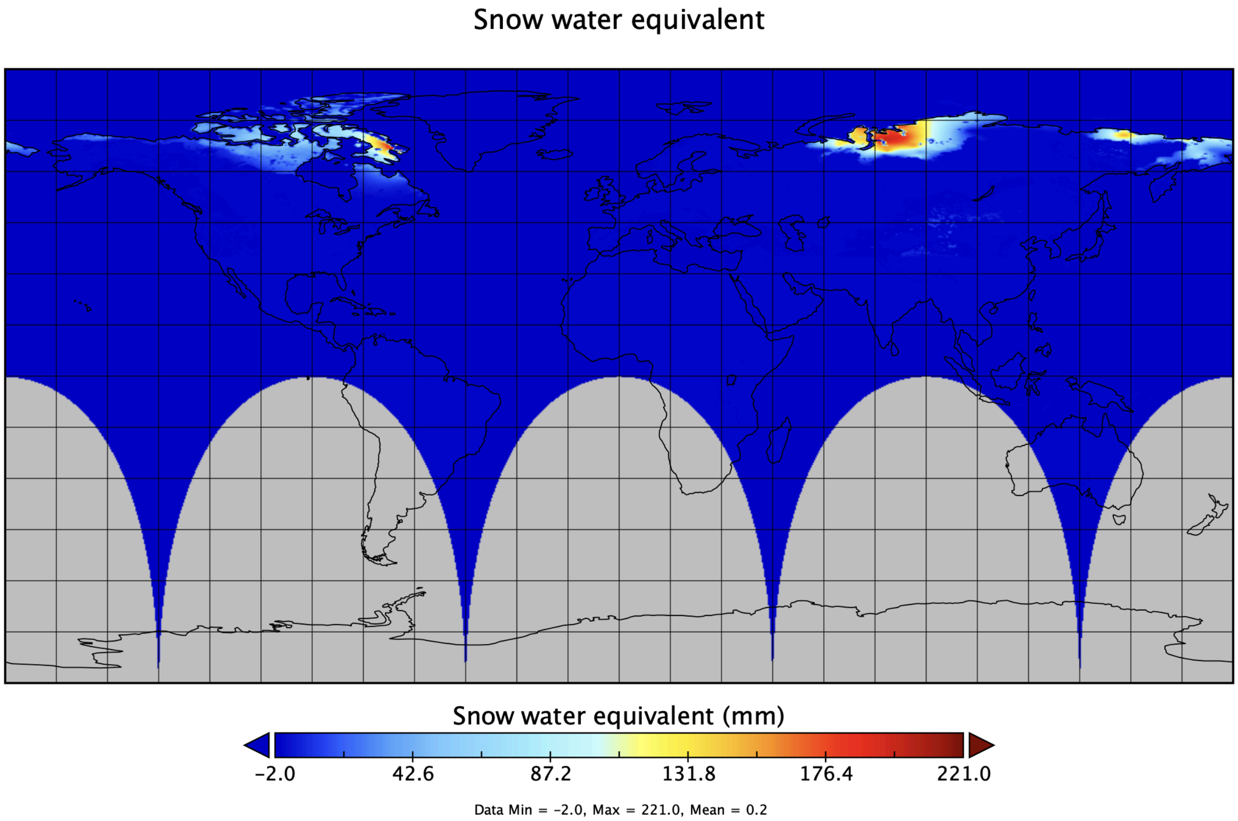

Figure 4. GlobeSnow SWE data visualization

The Middle Atlantic River Forecast Center (MARFC), operated by the National Weather Service under the United States Department of Commerce, plays a crucial role in Snow Water Equivalent (SWE) monitoring through its comprehensive information and mapping services. The actual SWE value is generally estimated from total snow depth, observed liquid equivalent precipitation, and the amount of snowmelt. Field checks are infrequent, and estimation relies on a combination of observed data and meteorological inputs.MARFC provides maps displaying the latest SWE values in the Northern and Southern MARFC areas. These maps aid in visualizing the distribution of liquid water content within the snowpack, guiding monitoring models. MARFC's SWE and snow depth information is instrumental in hydrological monitoring. River models leverage this data to anticipate the release of water into river channels, crucial for managing water resources and preparing for potential flooding events.

The AMSR-E/Aqua Daily L3 Global Snow Water Equivalent EASE-Grids dataset is a part of NASA's Earthdata platform, specifically hosted by the National Snow and Ice Data Center (NSIDC). This dataset contains Level-3 Snow Water Equivalent (SWE) information, which includes SWE data and quality assurance flags mapped to Northern and Southern Hemisphere 25 km Equal-Area Scalable Earth Grids (EASE-Grids).

1.4 The Usage of ML in SWE research

The integration of Machine Learning (ML) techniques into Snow Water Equivalent (SWE) monitoring offers several advantages. ML excels at handling large and complex datasets, making it well-suited for SWE prediction, where numerous variables such as meteorological data, terrain characteristics, and historical SWE records need to be considered. ML models can identify patterns and nonlinear dependencies within these datasets, potentially leading to more accurate predictions compared to traditional empirical or physics-based models (Fig. 5). Moreover, ML has the adaptability to handle changing environmental conditions, which is essential in a world where climate variability is on the rise. Thus, ML-based SWE estimation can be a valuable tool for optimizing water resource management, flood control, and ecological conservation.

Figure 5. SWE estimation Goal

1.5 Current Challenges for ML Approach

However, there are also some challenges associated with the use of ML in SWE estimation. One notable concern is the "black box" nature of many ML algorithms, which can make it difficult to interpret the underlying mechanisms driving the predictions (Gonzalez et al., 2019). This lack of interpretability may limit the ability of scientists and stakeholders to fully understand and trust the model's outputs. Additionally, ML models require large amounts of high-quality training data, and obtaining such data can be challenging in remote snow-dominated regions Particularly in mountainous regions, the spatial distribution of Snow Water Equivalent

(SWE) exhibits significant variability due to the interplay of complex geographical features and atmospheric conditions (Molotoch et al., 2005). There is also a risk of overfitting, where the model performs well on training data but fails to generalize effectively to new, unseen data. Furthermore, ML models are computationally intensive and may require significant computational resources for training and inference, which could be a limitation for some applications. A thoughtful integration of ML techniques, combined with domain knowledge and validation procedures, can harness the power of machine learning effectively for more informed decisions in snow-dominated regions.

In light of the potential and struggles that machine learning holds for SWE estimation, this review paper is dedicated to a meticulous examination of the current state of machine learning methodologies in SWE research. We will scrutinize a comprehensive selection of studies, spanning from both foundational works and the most recent advancements. We aim to elucidate the strengths, limitations, and overarching trends in machine learning applications within the field of hydrology and environmental science, specifically with regard to SWE estimation. By providing an exhaustive assessment of existing literature and a critical synthesis of machine learning's role in SWE prediction, this review endeavors to offer a well-informed foundation for researchers, practitioners, and policy-makers alike. In doing so, we strive to contribute to the ongoing discourse surrounding the effective utilization of machine learning in enhancing our understanding of SWE and its broader implications for water resource management and environmental sustainability.

2. Historical Development of SWE Monitoring Methods

2.1 Empirical Methods

The historical development of Snow Water Equivalent (SWE) monitoring methods reflects a gradual shift from rudimentary, empirical techniques to more sophisticated and data-driven approaches. This evolution has been essential in improving the accuracy and scope of SWE predictions, enabling better water resource management and flood risk assessment. In the early stages of SWE estimation, particularly during the mid-20th century, researchers and hydrologists heavily relied on empirical relationships, as elucidated by Anderson in his seminal work in 1976 (Anderson, 1976). These early methods were primarily founded on local observations of snow depth and SWE. Hydrologists would gather data from specific sites or regions and use these localized measurements to make predictions about SWE at those specific locations. While these methods provided some insight into snowpack characteristics, they had severe limitations when it came to extending these findings to larger geographical areas or basins. This restriction stemmed from the fact that SWE distribution can vary significantly across different landscapes due to factors like topography, climate, and land cover. A notable turning point in the historical development of SWE estimation methods came with the work of Martinec in 1975 (Martinec, 1975). His introduction of the degree-day method represented a significant departure from purely empirical approaches. This method marked a shift toward incorporating meteorological data, particularly temperature, into SWE estimation. The degree-day method recognized that temperature plays a crucial role in the snowpack's behavior, as it governs the rate at which snow accumulates and melts. The degree-day method essentially calculates the amount of snowmelt based on the accumulation of degree-days, which is a measure of temperature over time. By considering temperature data, hydrologists could make more accurate predictions about the timing and magnitude of snowmelt, which directly relates to SWE. This innovation showed promise in providing more accurate SWE predictions, especially in regions with well-documented temperature records.

2.2 Physics-Based Methods

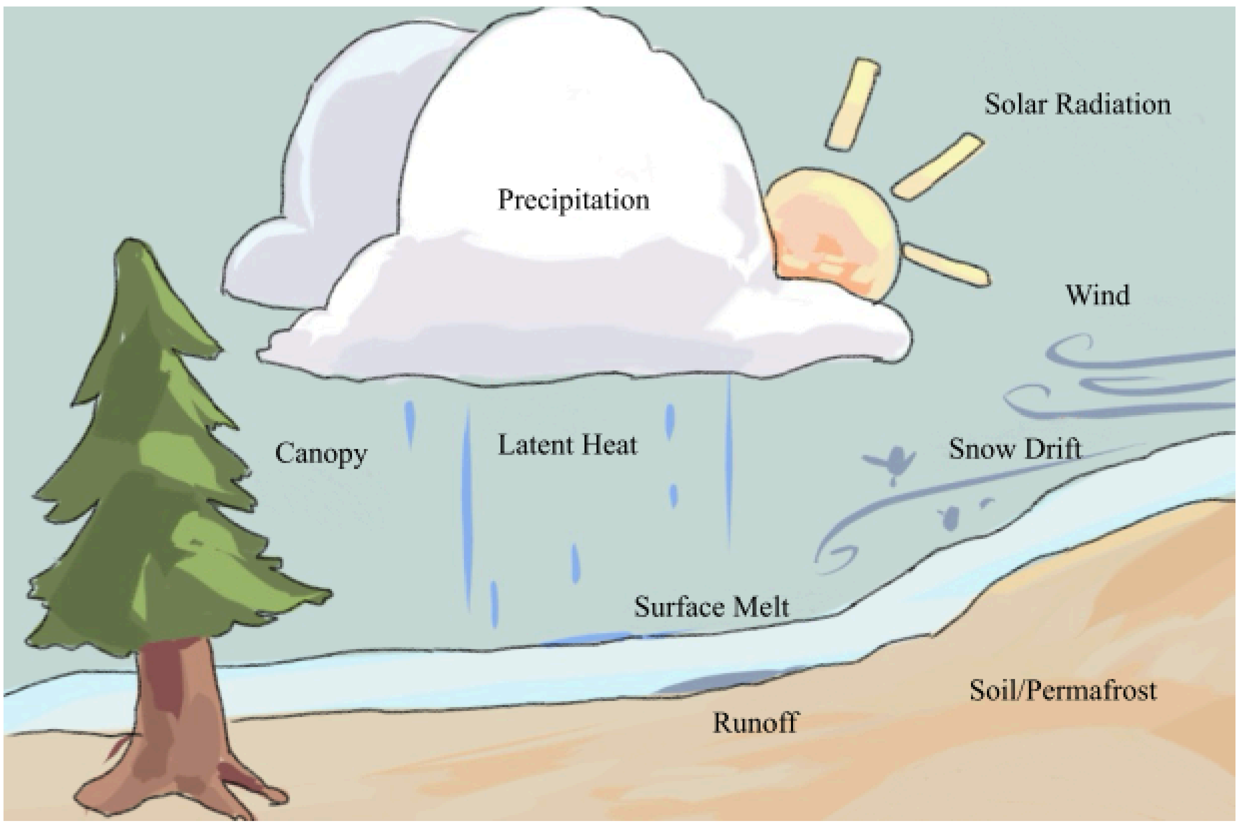

Figure 6. SWE Physics Model

Traditional hydrological models have played a crucial role in Snow Water Equivalent (SWE) monitoring, providing a solid foundation for understanding and predicting snowpack dynamics (illustrated in Fig. 6). Modern SWE estimation models like Snow17 and Snowpack models have emerged as powerful tools for estimating SWE. These models employ a physically-based approach to simulate the accumulation and melt of snow in a given area, integrating various meteorological data and snowpack properties to estimate SWE accurately. They utilize the energy balance equation to describe the transfer of energy within the snowpack, simulating the snow melting and accumulation processes. The basic energy balance equation is given by:

$$dH/dt = P - ET - Melt \quad (1)$$

where H represents the snowpack height, t is time, P is precipitation, ET is evapotranspiration, and melt represents the energy available for melting.

The Snow17 model builds upon the energy balance equation and is widely recognized for its accuracy in SWE estimation. It is grounded in the fundamental principles of snowpack physics, taking into account variables such as temperature, precipitation, solar radiation, and snow density to simulate the snowpack's behavior over time. One key component is the formulation of the degree-day factor (DDF) for snowmelt, often expressed as:

$$Melt = DDF \bullet \Delta T \qquad (2)$$

Where ΔT is the temperature difference from the snowmelt threshold. The model accounts for variations in solar radiation, snow density, and other parameters, enhancing its accuracy. The temporal evolution of SWE (SWE_{t+1}) in the Snow17 model is described by:

$$SWE_t = SWE_{(t-1)} + Snowfall - Snowmelt - Sublimation + Rainfall +$$

$$Snowpack\,Settlement + Runoff + Drifting + Redistribution \qquad (3)$$

Where SWE_t represents the amount of water within the snowpack at time t, while $SWE_{(t-1)}$ signifies the preceding time step's SWE value. Snowfall denotes the accumulation of new snow during the time step, while Snowmelt reflects the amount of snow that melts, often calculated using the degree-day factor (DDF) considering temperature differences. Sublimation accounts for snow transitioning directly to water vapor, influenced by temperature, humidity, wind speed, and solar radiation. Rainfall represents the amount of liquid precipitation, impacting snowmelt and snowpack properties. Snowpack Settlement refers to the compression of the snowpack due to accumulated weight, altering density and structure. Runoff describes melted snow water flowing over the snowpack's surface, influenced by slope and soil characteristics. Drifting denotes snow movement due to wind, altering snow distribution. Redistribution refers to snow movement within the pack, affected by wind, gravity, and temperature gradients, leading to spatial variations in depth and density. This equation is also considered as the mass balance equation. One of its notable strengths is its ability to capture the temporal evolution of SWE, allowing for precise tracking of snow accumulation during winter and subsequent snowmelt in spring and summer. Snow17 can also incorporate basin-specific parameters such as topography and vegetation cover, making it adaptable to a wide range of geographic regions.

Originally developed for avalanche warning (Lehning et al., 1999), The SNOWPACK model is another advanced tool for SWE estimation, particularly in regions with complex terrain and diverse snowpack conditions. The SNOWPACK model extends the physics-based approach, employing a multi-layer snowpack model. Each layer is characterized by specific physical properties, allowing for a more detailed representation of the snowpack. The model's snow water equivalent simulation involves equations for snow accumulation and ablation, considering factors such as heat conduction, radiation, and snow metamorphism. One key equation describing the change in snowpack energy content (ΔQ) is:

$$\Delta Q = \frac{\partial Q}{\partial t} = Q_{in} - Q_{out} + Q_{met} \tag{4}$$

where Q_{in} and Q_{out} are incoming and outgoing heat fluxes, and Q_{met} represents the metabolic heat production within the snowpack. This equation is also referred to as the energy balance equation. These models utilize complex algorithms to simulate the snowpack's behavior, incorporating meteorological variables, remote sensing data, and ground-based measurements to estimate SWE accurately. They offer flexibility in spatial resolution, capturing fine-grained variations in SWE. They find applications in avalanche monitoring, water resource management, and assessing snow-related hazards, particularly in mountainous regions.

2.3 Data Driven Methods

Data-driven methods are transforming the way we predict snow water levels. By analyzing historical and real-time data, these methods help us make more accurate forecasts of snow water equivalent (SWE). These methods encompass a variety of techniques, including regression analysis, machine learning algorithms such as Random Forest, Support vector machines (SVM) and Neural Networks like Long Short-Term Memory (LSTM). Regression analysis establishes a statistical relationship between various influencing factors such as temperature, precipitation, and topography. For instance, (Yang et al., 2022) utilized Linear regression models (LRMs) to correlate predictor variables with SWE measurements. This methodology enabled the reconstruction of historical SWE values and the examination of climate change effects on future SWE quantities. Regression models aid in comprehending the intricate factors affecting SWE and serve as a tool for both monitoring and historical reconstruction of snowpack levels. By identifying predictor variables, gathering data, conducting regression analysis, validating the model, and updating it over time, regression models offer valuable insights into SWE dynamics and enhance decision-making in hydrological management.

Machine learning algorithms, on the other hand, excel at capturing complex patterns and non-linear relationships, enabling them to generate precise forecasts even in the presence of noisy data. For instance, (Vafakhah et al., 2022), the Random Forest (RF) machine learning algorithm was employed to predict snow water equivalent (SWE) in the Sohrevard watershed in Iran. RF constructs multiple decision trees and combines their predictions to create a robust model. In this study, nine geo-environmental variables including altitude, slope, eastness, profile curvature, plan curvature, solar radiation, Topographic Position Index (TPI), Topographic Wetness Index (TWI), and wind exposition index were utilized as influencing factors for SWE prediction. The RF algorithm was applied with Latin Hypercube Sampling (LHS), which divides input data into intervals and randomly selects samples to create a more representative sample space, reducing bias and improving predictive performance. The RF algorithm's predictive capability was evaluated using error metrics such as r, RMSE, MAE, and PBIAS, with results indicating its effectiveness in both training and testing stages. The RF algorithm demonstrated high accuracy in predicting SWE levels in the Sohrevard watershed, suggesting its potential applicability to similar watersheds.

Artificial Neural Networks offer a data-driven approach to predicting Snow Water Equivalent by learning complex relationships from various sources, such as snow depth measurements and meteorological indicators (air temperature, precipitation, solar radiation). For instance, (Thapa et al., 2024), demonstrated how specific types of ANNs, such as the Long Short-Term Memory (LSTM) networks are trained on time-series data of snowpack and snowmelt variables, and learn to recognize patterns in the data. By identifying patterns within this data, LSTM models are able to predict future SWE values accurately. Additionally, LSTM models can handle long-term dependencies and can capture changes in SWE that occur over extended periods. Moreover, ANNs are capable of understanding correlations across different locations and time frames, enhancing the accuracy of SWE forecasts. Overall, data-driven methods offer a flexible and powerful framework for SWE estimation, allowing for the integration of diverse data sources, adaptation to changing conditions, and the capture of complex relationships in the data for more accurate predictions, critical for effective water resource management and environmental planning.

The evolution of snow water equivalent (SWE) monitoring methods has progressed from early empirical techniques and physics-based models, such as Snow17 and Snowpack, towards more advanced data-driven approaches. Empirical techniques, rooted in historical observations and statistical relationships, laid the foundation for understanding SWE dynamics (Leisenring and Moradkhani , 2011). Statistical models, including time series analysis and autoregressive models, leveraged historical data to identify patterns and trends in SWE behavior (Sarhadi et al., 2014). Hybrid models seamlessly integrated empirical knowledge and data-driven techniques, combining the strengths of both approaches to enhance SWE predictions (Brown, R. D. et al., 2003).

The integration of remote sensing data has significantly contributed to data-driven SWE estimation by providing valuable insights into snow cover extent and density (Marks and Dozier, 1992). Within the data-driven realm, machine learning techniques, such as supervised learning, unsupervised learning, and deep learning, have emerged as powerful tools to model complex relationships within SWE data (Zhang et al., 2021). Ensemble methods, another data-driven category, capitalize on combining multiple models to improve overall monitoring accuracy by mitigating individual model uncertainties (Diks and Vrugt, 2010). As we explore these methodologies in detail, it becomes evident that the progression from empirical to data-driven approaches has greatly enhanced the accuracy and scope of SWE predictions, offering valuable insights for water resource management and decision-making in snow-dominated regions.

3. Current Machine Learning-based SWE estimation Research

3.1 Early Endeavors (2000-2014)

Machine learning techniques have undergone a remarkable evolution within the field of hydrology, especially in the context of Snow Water Equivalent (SWE) monitoring (Table 1). This evolution has been marked by significant advancements in modeling capabilities, allowing for more accurate and data-driven predictions of SWE dynamics. Dawson and Wilby (2001) played a pioneering role in showcasing the potential of artificial neural networks (ANNs) for hydrological modeling, which extends to SWE estimation. ANNs, characterized by their ability to capture intricate non-linear relationships within data, have since become a cornerstone of machine learning applications in hydrology. By harnessing the power of ANNs, researchers have been able to model the complex interplay of meteorological variables, snowpack properties, and basin-specific characteristics, resulting in more accurate SWE forecasts. Building on the foundation laid by ANNs, Shrestha et al. (2006) introduced decision trees as an alternative approach in hydrological modeling. Decision trees are particularly well-suited for their ability to handle both numerical and categorical data, making them adaptable to the diverse array of variables influencing SWE. Similarly, Lin et al. (2006) introduced support vector machines (SVMs) to the hydrology community. SVMs excel in capturing intricate patterns and have proven to be valuable tools in SWE estimation, contributing to the diversification of machine learning techniques available in this field. Further enhancing the arsenal of machine learning tools, Chen et al. (2016) brought random forests to the forefront of SWE estimation. Random forests are renowned for their ensemble learning capabilities, which enable them to combine the predictive strengths of multiple decision trees. This ensemble approach has substantially improved the robustness of SWE forecasts, especially in regions characterized by varying snowpack characteristics, where predicting SWE accurately is particularly challenging.

The incorporation of these diverse machine learning techniques into SWE estimation has ushered in a new era of modeling capabilities. These algorithms excel in capturing the intricate relationships between meteorological data and SWE dynamics, allowing for more precise predictions and greater adaptability to diverse environmental conditions. In the following section, we will delve into recent research that has harnessed these machine learning techniques, offering insights into their real-world applications and the benefits they bring to SWE estimation. This evolution in modeling approaches underscores the potential for continued advancements in SWE estimation accuracy and our ability to address critical water resource management challenges.

Table 1. Previous Work of ML in SWE research

Author	Year	Model	Summary	Accuracy	Region
Dawson and Wilby	2001	Artificial Neural Networks (ANNs)	Demonstrated the immense potential of artificial neural networks (ANNs), known for their ability to capture	ANN can capture the complex spatial and temporal patterns of the hydrological process	ANN models can be utilized as an effective tool for hydrological

			intricate non-linear relationships within data. They laid the foundation for subsequent advancements in machine learning applications within hydrology.	and produce high-accuracy predictions.	modeling in various geographic regions and hydrological environments.
Shrestha et al	2006	Decision trees	Decision trees are effective in hydrology, offering a simple and interpretable approach to construct models and forecast future events. They handle complex relationships well, providing estimation of prediction intervals for uncertainty quantification	Decision trees can accurately handle large numbers of input variables and their interpretability.	In addition to hydrological modeling and prediction, Decision trees are also applicable in Finance, marketing, and environmental modeling.
JIAN-YI LIN	2006	Support Vector Machines (SVM)	The SVM model can give good prediction performance, especially in hydrological systems, by maximizing the margin between the input-output pairs and identifying the best decision boundary between the classes, which can help identify patterns and relationships in the data.	The SVM excels at generating accurate predictions within hydrological systems, primarily by reducing overfitting and delivering optimal solutions. Its effectiveness,however, depends on the correct selection of parameters, and training data.	SVM is applied in different fields such as hydrological prediction, anomaly detection, image classification, text classification, and pattern recognition.
Wade T. Tinkham	2014	Random Forest	The study explores the utilization of random forest modeling to forecast Snow Water Equivalent (SWE) in complex terrains. The author employs topographic surveys for various snow-related variables, aiming to identify factors affecting SWE prediction while also computing error bounds for catchment snow volume.	The Random Forest model demonstrated a high level of accuracy in predicting both the lower and upper bounds of the theoretical catchment snow volume error.	While the author focuses on Random Forest for SWE prediction, it's recognized that Random Forest has diverse applications, including remote sensing, ecology, and epidemiology.

Buckingham , Skalka, Bongard: https://meclab.w3.uvm.edu/papers/2015_JHydro_Buckingham.pdf	2015	Genetic Programming (GP)	While infrastructure for collecting SWE data exists, spatial variability makes accurate estimation challenging. The authors propose low-cost, lightweight methods for near-real-time catchment-wide SWE estimation using existing infrastructure and wireless sensor networks. They focus on Genetic Programming (GP), a nonlinear, inductive machine learning algorithm. By comparing GP with linear regression and other methods, they demonstrate improved SWE prediction accuracy.	Genetic Programming (GP) improves the accuracy of estimating mean catchment-wide Snow Water Equivalent (SWE) from single-point measurements by incorporating new predictors of catchment-scale SWE into its models. By using relevant input data and ignoring irrelevant data, GP enhances the accuracy of SWE estimation.	Genetic Programming (GP) can be applied in image processing, object recognition of satellite data, soil hydraulic conductivity estimation, and time series analysis.
Ghanjkhanlo, Zeinivand & Fathzadeh	2020	Artificial Neural Network (ANN) with the hyperbolic tangent function	Access to snow distribution in snowy areas is important because of its use in water resource management in mountainous areas; however, because of safety issues it is difficult to directly measure SWE. Instead, they found after testing various algorithms (decision tree, support vector machine, adaptive neuro-fuzzy inference system) that ANN outperformed the other models.	They found the ANN was better at predicting nonlinear phenomena.	ANN models can be used for snow dominated mountainous areas. This is because it is able to model the nonlinear trend of snow spatial distribution.
Durand et al.	2008	Bayesian Reconstruction Data Assimilation Scheme	They use a Bayesian SWE reconstruction that combines a time series of remote sensing estimates of a snow-covered area with a land surface model, Simplified Simple Biosphere Model version 3. They found this technique shows promise in characterizing spatial patterns of snowfall over	Found this model increased mean and standard deviation of the SWE estimate error by 86% and 78%.	This model is used for seasonal SWE accumulation in mountainous regions

			mountainous regions.		
Leisenring & Moradkhani	2011	SNOW-17 using the particle filter	To predict seasonal SWE they used various data assimilation methods for SNOW-17: ensemble Kalman filter (EnkF), the ensemble square root filter (EnSRF), and four variants of the particle filter (PF). The results suggest that the particle filter is superior to the other methods for predicting model states and model parameters.	Depending on ensemble size there were various improvements. No matter what particle filters outperformed Kalman filter methods with mean and interval predictions of SWE.	This model is used for places near water e.g lakes and creeks.

3.2 State of the Art (Status Quo) (2014-present)

Accurate Snow water equivalent (SWE) prediction is essential for various sectors, including water resource management, agriculture, and flood forecasting. However, traditional estimation models face significant challenges due to the complexities inherent in snow accumulation and melting processes. Recent studies have demonstrated the effectiveness of machine learning (ML) in addressing these challenges (Taheri et al., 2022). One of the main challenges in SWE prediction is related to the limited spatial and temporal coverage of in-situ measurements, which hinders the accuracy of most SWE estimation approaches. This is where ML can help. ML algorithms, such as neural networks, can learn from a large amount of input data, such as remotely sensed images and meteorological data, to make accurate predictions of SWE. These models can consider the complex interactions between different snow variables and environmental factors to improve SWE estimation.

The limited availability of data poses a significant challenge in snow-water equivalent (SWE) prediction. However, ML models offer a solution to this data scarcity issue by using algorithms that can reliably estimate SWE even with limited data availability. Traditional SWE prediction methods require large amounts of training data, which can be difficult to obtain in regions with limited data availability. Recent advances in ML techniques, including Random Forest (RF), Support Vector Machine (SVM), and deep learning (DL), have shown promising results in SWE prediction (Schilling et al., 2024). These models can utilize various data sources such as satellite images, weather, and climate data to improve the accuracy of SWE estimation, even when ground-truth data is unavailable. ML models can be trained with a subset of available data to predict SWE in regions where data is scarce.

Temporal variability and short-term fluctuations, known pain points for conventional SWE models, find respite in ML techniques. ML facilitates temporal modeling, capturing the dynamic evolution of snowpack behavior over time. Furthermore, the application of ensemble estimation through ML, which amalgamates multiple methods, significantly bolsters the reliability of predictions, particularly in scenarios characterized by rapid changes. Significant advancements are exemplified by studies like that of Zhao et al. (2018), which introduces hybrid models combining the Snowmelt Runoff Model with ML components. These hybrid models showcase tangible improvements in accuracy and flexibility in SWE estimation. The synergistic integration of physical principles and ML's adeptness in capturing complex relationships marks a paradigm shift in estimation approaches.

The integration of remote sensing data into ML models, as showcased by Mudelsee et al. (2018), elevates the spatial and temporal resolution of SWE forecasts. ML-driven processing of satellite-based observations significantly improves the precision of real-time monitoring and predictions, especially in regions where ground-based measurements are limited. Ongoing research endeavors are meticulously addressing specific challenges within different environmental contexts. By focusing on refining ML methods and advancing our understanding of SWE dynamics, the collaboration between physically based models and ML techniques, enriched by remote sensing data, promises further advancements in SWE estimation capabilities. This holds particular significance for regions characterized by intricate and diverse conditions, where traditional methodologies fall short.

Recent research in Snow Water Equivalent (SWE) estimation has witnessed notable advancements through the application of machine learning techniques. These innovations have enhanced our ability to predict SWE accurately, which is crucial for various applications, including water resource management, flood risk assessment, and ecological studies. One promising avenue in recent research involves the development of hybrid models that combine the strengths of physically based models with machine learning algorithms. Zhao et al. (2018) made significant contributions in this regard. They introduced a hybrid model that integrated the Snowmelt Runoff Model (SRM), a well-established physically based model, with a machine learning component. This fusion of approaches resulted in a model that demonstrated enhanced accuracy and flexibility in SWE monitoring. The hybrid model effectively leverages the physical principles governing snowmelt processes while also harnessing the capacity of machine learning to capture complex relationships and patterns within the data. By doing so, it overcomes some of the limitations of purely physically based models, which may struggle to account for intricate nonlinear interactions in the system. This approach represents a promising step forward in SWE estimation, offering the potential for more reliable and adaptable predictions.

The application of deep learning methods has also been explored in recent research, specifically Long Short-Term Memory (LSTM), in improving SWE simulations. In a study focused on the western US, an LSTM network with data integration (DI) was tested. This involved integrating 30-day-lagged or 7-day-lagged observations of either SWE or satellite-observed snow cover fraction (SCF) to improve future predictions. The results showed that lagged SWE integration significantly improved prediction accuracy for both shallow and deep snow sites. The use of LSTM, combined with 30-day-lagged SWE integration, led to notable improvements, including an increase in the median Nash-Sutcliffe model efficiency coefficient (NSE) from 0.92 to 0.97. Data integration effectively mitigated accumulated model and forcing errors, revealing differences in spatial distribution with varying lag lengths. For example, integrating 30-day-lagged SWE was less effective for ephemeral snow sites but significantly reduced biases for regions with stable seasonal snowpack. The study establishes benchmark levels and provides guidance for future model improvement strategies. Understanding the spatial and temporal impact of lagged observations on SWE predictions is crucial for refining models and addressing persistent errors.

4. ML Benefits and Bottlenecks

Despite the promising developments in SWE estimation, several critical gaps remain in the field. These gaps highlight areas where further research and improvements are needed to advance the accuracy and applicability of SWE predictions.

Table 2. Side-by-side comparison of traditional approach and ML approach

	Traditional SWE estimation Methods (numeric models, e.g., SNOW17, SNOWPACK,)	**ML-based SWE estimation Methods (e.g., linear regression, SVM, random forest, neural network, deep learning, reinforcement learning, etc)**
Accuracy	***Pros***: Traditional SWE estimation, particularly when relying on ground-based measurements, can be highly accurate at a local scale. ***Cons***: In regions with complex terrain, traditional methods may face challenges in accurately capturing spatial variations in SWE, leading to potentially less accurate forecasts. The impact of localized topographical features can be significant. Traditional methods are subject to human errors in data collection and measurement, which can affect accuracy. The accuracy is contingent on the training and expertise of the personnel collecting the data.	***Pros***: ML-based SWE estimation can provide accuracy at various spatial scales, from local to regional or even global. With the right data sources and models, ML methods can offer precise estimates of SWE for a range of areas. ML models, especially when trained on high-resolution data and complex algorithms, can better adapt to complex terrain and capture fine-grained variations in SWE. This adaptability can enhance accuracy, even in regions with significant topographical diversity.
Spatial Resolution	***Cons***: Traditional SWE estimation often relies on lower spatial resolutions, particularly for data collected from ground-based measurements, such as snow surveys and weather stations. These measurements are typically point-based and represent a local area's SWE accurately but lack extensive spatial coverage.	***Pros:*** ML-based SWE estimation has the flexibility to work with a range of spatial resolutions. It can incorporate both high-resolution remote sensing data and lower-resolution ground-based data, depending on the data sources available and the specific needs of the forecast. ML models trained on high-resolution data can capture fine-grained variations in SWE, resulting in more accurate forecasts, especially in regions with complex terrain or spatial variability.
Data Integration	***Cons***: Traditional SWE estimation often relies on manual or semi-manual data collection methods, such as snow surveys or ground-based measurements. These methods require fieldwork and human intervention to gather data. Data	***Pros***: ML-based SWE estimation can integrate a wide range of data sources, including remote sensing imagery, weather data, ground-based measurements, and additional environmental data. This diversity of data sources allows for a more

	integration in traditional SWE estimation is typically straightforward, with a focus on combining data from a few predefined sources. Integration is often accomplished using manual processes or simple data management techniques.	comprehensive understanding of snowpack conditions. ML models can automatically process and integrate data from various sources, enabling more efficient and continuous data analysis. This automation can handle large volumes of data and respond to changes in real-time.
Automation	***Cons***: Typically requires manual intervention for data interpretation. Heavily depends on the quality and reliability of input data. Automated systems may not have the capability to assess and correct data issues.	***Pros***: Can automate data analysis and estimation processes. ***Cons***: ML models require significant data preprocessing efforts, including data cleaning, feature engineering, and normalization. Handling diverse data sources and ensuring data quality can be time-consuming and resource-intensive.
Adaptability	***Cons***: Traditional SWE estimation methods often have limited adaptability to changing conditions. They rely on static, point-based measurements, which may not capture dynamic variations in snowpack over time.	***Pros***: ML-based SWE estimation is highly adaptable to changing conditions. ML models can continuously learn and adjust to new data, making them capable of capturing dynamic variations in snowpack and responding to evolving weather patterns.
Data Requirements	***Cons***: Traditional methods often rely on sparse, localized data points, such as ground-based measurements from snow surveys, snow pillows, or weather stations. The data typically represent a limited number of locations.	***Pros***: ML-based estimation requires diverse data sources, including remote sensing imagery, weather data, ground-based measurements, and possibly additional environmental data like soil moisture and topography. ML models thrive on large volumes of data. To make accurate predictions, they require substantial datasets, often spanning multiple years and covering a wide geographic area. Data requirements for ML-based methods often involve data pre-processing steps, such as cleaning, normalization, and feature engineering, to prepare the data for modeling.
Cost	***Pros***:	***Pros:***

	Traditional methods generally have lower initial setup costs. They often rely on well-established techniques and equipment, such as snow surveys, weather stations, and manual data collection, which are relatively inexpensive to implement. Traditional methods may not require significant investments in advanced technology, data processing, or software development, which can reduce costs. ***Cons***: Operation or experiment costs are very high. (expand with one or sentence)	Its overall ratio, investment over accuracy and operation costs, is lower than traditional methods[1]. ***Cons***: ML-based SWE estimation often has higher **initial setup costs** due to the need for advanced technology and data processing infrastructure. This includes the cost of remote sensing equipment, data storage, and computing resources. ML methods may require access to various data sources, some of which could incur expenses. For example, high-resolution satellite imagery or specialized sensors can have associated data acquisition costs.
Suitability for Remote Areas	***Pros:*** Often rely on well-established methods and historical data. These methods have been used for many years and have a proven track record in various regions.Some approaches involve on-the-ground measurements, such as snow surveys and manual observations. ***Cons:*** In such regions, it is challenging to obtain sufficient ground-based measurements to make accurate forecasts. Traditional approaches may suffer from a temporal lag between data collection and estimation, which can impact the timeliness of flood or water resource management decisions. In remote areas, data uncertainty can be a significant challenge. Sparse data coverage, inconsistent measurements, and difficulties in accessing measurement sites can lead to uncertainties in estimation.	***Pros:*** AI algorithms can analyze vast and complex datasets, including remote sensing data, climate data, and historical records, to identify patterns and relationships that may not be evident using traditional methods. This can lead to more accurate SWE forecasts. AI methods can process real-time and high-frequency data, allowing for more up-to-date SWE forecasts. This timeliness is particularly valuable in remote areas where conditions can change rapidly. Remote sensing technologies provide extensive spatial coverage, enabling AI models to generate forecasts for remote and inaccessible regions where traditional ground-based measurements are limited. They excel at integrating multiple data sources, such as satellite imagery, weather data, and topographic information. This comprehensive approach improves estimation precision. ***Cons:*** The accuracy of AI forecasts is highly dependent on the quality of input data. In remote regions, data quality issues, such as sensor calibration errors or data gaps, can compromise the reliability of AI-driven forecasts. AI models,

[1]

		particularly deep learning models, are often regarded as "black boxes" with limited interpretability. Understanding the underlying processes and factors influencing SWE forecasts can be challenging.
Historical Data Availability	***Pros:*** Traditional methods often rely on established formulas and empirical relationships that have been developed and validated over time, requiring less historical data for training and calibration.	***Pros:*** ML methods can effectively incorporate diverse sources of historical data, such as satellite imagery, climate records, and remote sensing data, allowing for a comprehensive understanding of past conditions. ML algorithms can often handle missing or incomplete historical data more effectively than traditional methods, allowing for more robust utilization of available information. ***Cons:*** ML models, particularly deep learning models, may require large amounts of historical data for effective training. In situations with limited historical records, the model's performance may be compromised.
Human Expertise	***Pros:*** Human expertise in traditional SWE estimation methods often draws from historical knowledge and experience. Experts have accumulated insights and techniques over years or even generations, which can be valuable for understanding local snowpack conditions. Experts can interpret data collected from ground-based measurements, snow surveys, and manual observations. They can identify nuances and patterns that automated systems may overlook, contributing to more accurate interpretations of the data. ***Cons:***	***Pros***: Requires expertise in data preprocessing, feature engineering, model selection, and validation. Scientists have to enhance their data science capabilities. SWE AI scientists can quickly adapt to changing data sources and patterns, allowing for more flexible and responsive estimation. SWE scientists may have interdisciplinary expertise exposure, understanding both the domain-specific aspects of SWE estimation and the technical aspects of AI/ML. With the right expertise, AI/ML models can be trained and deployed faster than developing complex numerical models. Scientists can set up real-time monitoring systems, enabling quick responses to changing conditions.

	Traditional methods that rely on human expertise may not be easily scalable to cover larger geographic areas or regions with complex terrain. They often require a workforce of experts, which can be resource-intensive to train them and some knowledge may not be applicable in remote or understaffed areas. The accuracy of traditional SWE estimation methods heavily depends on the quality and reliability of human input. Human errors in data collection and measurement, as well as biases in interpretation, can affect the accuracy of forecasts.	***Cons:*** Developing and maintaining AI/ML models requires a high level of technical expertise, which may not be readily available in traditional scientific roles. Scientists need to understand data quality issues, including potential biases and errors in training data. Choosing the right machine learning algorithms and hyperparameters is a non-trivial task, which can lead to suboptimal results if not done correctly. Ensuring that AI/ML models provide accurate and reliable forecasts requires continuous validation and monitoring, which can be resource-intensive. Scientists need to address ethical concerns like bias, fairness, and transparency in AI/ML models, which may involve a different skill set compared to traditional modeling.
Speed	***Pros:*** Traditional methods often have simpler mathematical formulations, leading to faster computation times compared to complex AI/ML models, making them suitable for quick and routine SWE forecasts. Methods like SNOW 17 and SNOWPACK have been well-established and widely used in the scientific community, providing a reliable and standardized approach for SWE estimation. Unlike machine learning models, traditional methods don't require extensive training periods. They are often parameterized based on physical principles, reducing the time needed for model setup and calibration. ***Cons***: Calibration of traditional models like SNOW 17 and SNOWPACK may require manual adjustment of parameters, which can be time-consuming and dependent on expert knowledge. Traditional methods may struggle to adapt to changing	***Pros:*** AI/ML algorithms can quickly process large datasets, enabling faster analysis and estimation compared to traditional methods. They can leverage parallel processing capabilities, allowing them to handle complex computations simultaneously and speed up the estimation process. ML models can automate the estimation process, reducing the need for manual intervention and speeding up the overall workflow. ***Cons:*** Preparing data for ML models often involves extensive preprocessing, which can contribute to delays in estimation speed, especially when dealing with diverse and large datasets. Some advanced AI/ML models may have high computational requirements, leading to longer processing times, especially if the hardware infrastructure is not optimized.

	environmental conditions or handle non-linear relationships, limiting their effectiveness in dynamic or complex scenarios.	
Forecasting Length	***Pros***: Traditional methods are often designed for longer-term forecasting and can maintain stability in predictions over extended periods. As they are often based on well-established physical principles, This stability can be advantageous for long-term forecasting. ***Cons***: In dynamic environments or regions with rapid climate changes, traditional methods may face challenges in accurately forecasting SWE over an extended period. Traditional methods may struggle to represent complex non-linear trends that become more pronounced over extended forecasting lengths.	***Pros***: ML methods, especially advanced algorithms, can capture non-linear relationships and patterns in data, making them well-suited for forecasting over extended periods where non-linear trends may emerge. ML models can efficiently integrate various types of data, including satellite imagery, climate data, and remote sensing, enhancing their ability to forecast SWE over longer time frames.ML models can continuously learn from new data, allowing them to adapt to changing environmental conditions and improving their forecasting accuracy over time. ***Cons***: ML methods heavily rely on the quality and quantity of training data. Inadequate or biased data can lead to inaccurate long-term forecasts.ML models, particularly when trained on abundant data, may risk overfitting, where the model performs well on training data but struggles with generalization to new, unseen data in long-term forecasting scenarios. ML models might degrade in performance over time if they are not regularly updated or retrained with new data, especially if the underlying environmental conditions change significantly.

5. Discussion and Future Directions

5.1 Generalized AI for SWE

In the pursuit of harnessing Generalized AI (AGI) for snow water equivalent (SWE) estimation and forecasting, we encounter significant challenges and limitations that must be addressed to realize its full potential. One key obstacle lies in the complexity of integrating diverse data sources and variables, which often results in information silos and interoperability issues. Additionally, AGI systems require vast amounts of high-quality labeled data for training, posing a challenge in domains such as snow hydrology where data availability may be limited or inconsistent. Moreover, ensuring the robustness and interpretability of AGI models is paramount, as inaccuracies or biases in the models can have far-reaching consequences for decision-making and resource management.

To overcome these challenges and achieve the promise of AGI in SWE research, interdisciplinary collaboration is essential. Bringing together experts from fields such as hydrology, meteorology, computer science, and data science enables a holistic approach to model development and validation. Moreover, investment in data infrastructure and collection efforts, including remote sensing technologies and ground-based observations, can help address data scarcity issues and improve the quality of training datasets. Additionally, research into novel algorithms and techniques for model interpretability and uncertainty quantification is crucial to enhance trust and reliability in AGI predictions.

Furthermore, fostering a culture of transparency and accountability in AGI development is essential. Open access to models, data, and methodologies facilitates peer review and validation, promoting trust and confidence in AGI systems. Moreover, ongoing monitoring and evaluation of model performance against ground truth observations allow for continuous refinement and improvement. By addressing these challenges and embracing a collaborative and transparent approach, we can unlock the transformative potential of AGI in SWE estimation and forecasting, empowering stakeholders with actionable insights for water resource management and climate resilience.

5.2 Self-learning Agent for SWE

The exploration of self-learning agents for snow water equivalent (SWE) is motivated by the quest for adaptive, autonomous systems capable of continuously improving performance in dynamic environments. By leveraging machine learning techniques such as reinforcement learning, these agents can learn from experience and iteratively refine their predictions based on feedback from observed outcomes. However, the development and deployment of self-learning agents in the context of SWE estimation pose several significant challenges. One primary challenge is the inherent complexity and uncertainty in snow hydrology processes, which may lead to suboptimal performance or unexpected behaviors in self-learning agents. Additionally, ensuring the stability and safety of autonomous agents in real-world applications is critical, as errors or inaccuracies in predictions can have significant consequences for water resource management and downstream stakeholders. Furthermore, the interpretability and transparency of self-learning agents remain a concern, as understanding the reasoning behind their decisions is essential for building trust and facilitating human-AI collaboration.

To address these challenges and realize the potential of self-learning agents for SWE estimation, interdisciplinary collaboration and robust validation frameworks are paramount. Collaborating with domain experts in snow hydrology and meteorology can provide valuable insights into the underlying processes and help guide the development of more accurate and reliable models. Moreover, employing techniques for uncertainty quantification and sensitivity analysis can help assess the robustness of self-learning agents and identify potential failure modes or edge cases. Furthermore, incorporating mechanisms for human oversight and intervention is crucial for ensuring the safety and reliability of self-learning agents in real-world applications. By designing systems that allow for human-AI collaboration and feedback, we can mitigate the risk of unintended consequences and promote responsible AI deployment. Additionally, investing in research on explainable AI techniques and model interpretability can enhance our understanding of self-learning agents' decision-making processes, fostering trust and transparency in their predictions.

5.3 Incorporating SWE AI into the Larger Earth AI Model

By incorporating SWE AI alongside other environmental data sources, such as satellite imagery, climate models, and geospatial data, we can develop more comprehensive and accurate models of Earth's hydrological cycle. However, this integration presents several challenges that must be addressed to realize its full potential. One significant challenge is the heterogeneity and scale of Earth observation data, which often come from disparate sources and exhibit varying levels of spatial and temporal resolution. Integrating SWE AI into a larger Earth AI model requires harmonizing and processing these diverse datasets to extract meaningful insights and relationships. Additionally, ensuring the scalability and efficiency of AI algorithms for processing large-scale Earth observation data is essential to enable real-time analysis and decision-making. Furthermore, the interdisciplinary nature of Earth systems modeling necessitates collaboration between experts from different fields, including hydrology, climatology, remote sensing, and AI. Bridging these disciplinary boundaries and integrating domain-specific knowledge into AI models is crucial for developing accurate and reliable Earth AI models. Moreover, establishing robust validation frameworks and uncertainty quantification techniques is essential for assessing the reliability and robustness of AI predictions in complex Earth systems.

To address these challenges and realize the potential of incorporating SWE AI into the larger Earth AI model, investments in data infrastructure, computational resources, and interdisciplinary collaboration are required. Leveraging advancements in cloud computing and distributed computing platforms can facilitate the processing and analysis of large-scale Earth observation datasets. Additionally, fostering open access to data and model outputs promotes transparency and reproducibility in Earth AI research, enabling broader participation and collaboration across the scientific community. Ultimately, by integrating SWE AI into a larger Earth AI model, we can gain deeper insights into the complex interactions and feedback mechanisms shaping Earth's hydrological cycle. Through interdisciplinary collaboration, robust validation, and scalable computing infrastructure, we can harness the power of AI to address pressing environmental challenges and advance our understanding of Earth's dynamic systems.

6. Conclusion

This paper overviews the historical development, current state, and future prospects of snow water equivalent (SWE) monitoring and forecasting methods, with a particular focus on machine learning (ML) approaches. We have observed the evolution from empirical and physics-based methods to the emergence and advancement of data-driven techniques, highlighting the significant role ML plays in enhancing SWE estimation accuracy. Despite the considerable progress made, several challenges persist, including the need for improved model interpretability, data quality, and scalability. Looking ahead, the future of SWE estimation lies in the integration of generalized artificial intelligence (AI) techniques, the development of self-learning agents tailored to SWE dynamics, and the incorporation of SWE AI into larger Earth AI models. By leveraging interdisciplinary collaborations and cutting-edge technologies, we can strive towards more accurate, efficient, and sustainable SWE estimation systems, contributing to better water resource management, climate change adaptation, and ecosystem resilience in snow-dominated regions.

Author Contributions

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References

Beria, Harsh, Joshua R. Larsen, Natalie Claire Ceperley, Anthony Michelon, Torsten Vennemann, and Bettina Schaefli. "Understanding snow hydrological processes through the lens of stable water isotopes." *Wiley Interdisciplinary Reviews: Water* 5, no. 6 (2018): e1311.

Krinner, Gerhard, Chris Derksen, Richard Essery, Mark Flanner, Stefan Hagemann, Martyn Clark, Alex Hall et al. "ESM-SnowMIP: assessing snow models and quantifying snow-related climate feedbacks." *Geoscientific Model Development* 11, no. 12 (2018): 5027-5049.

Anderson, Eric Andrew. *A point energy and mass balance model of a snow cover*. Stanford University, 1976.

Yang, Kehan, Keith N. Musselman, Karl Rittger, Steven A. Margulis, Thomas H. Painter, and Noah P. Molotch. "Combining ground-based and remotely sensed snow data in a linear regression model for real-time estimation of snow water equivalent." Advances in Water Resources 160 (2022): 104075.

Vafakhah, Mehdi, Ali Nasiri Khiavi, Saeid Janizadeh, and Hojatolah Ganjkhanlo. "Evaluating different machine learning algorithms for snow water equivalent prediction." Earth Science Informatics 15, no. 4 (2022): 2431-2445.

Thapa, Krishu K., Bhupinderjeet Singh, Supriya Savalkar, Alan Fern, Kirti Rajagopalan, and Ananth Kalyanaraman. "Attention-Based Models for Snow-Water Equivalent Prediction." In Proceedings of the AAAI Conference on Artificial Intelligence, vol. 38, no. 21, pp. 22969-22975. 2024.

Ntokas, Konstantin FF, Jean Odry, Marie-Amélie Boucher, and Camille Garnaud. "Investigating ANN architectures and training to estimate snow water equivalent from snow depth." Hydrology and Earth System Sciences 25, no. 6 (2021): 3017-3040.

Dawson, C. W., and R. L. Wilby. "Hydrological modeling using artificial neural networks." Progress in physical Geography 25, no. 1 (2001): 80-108.

Shrestha, Durga L., and Dimitri P. Solomatine. "Machine learning approaches for estimation of prediction interval for the model output." Neural networks 19, no. 2 (2006): 225-235.

Lin, Jian-Yi, Chun-Tian Cheng, and Kwok-Wing Chau. "Using support vector machines for long-term discharge prediction." Hydrological sciences journal 51, no. 4 (2006): 599-612.

Tinkham, Wade T., Alistair MS Smith, Hans-Peter Marshall, Timothy E. Link, Michael J. Falkowski, and Adam H. Winstral. "Quantifying spatial distribution of snow depth errors from LiDAR using Random Forest." *Remote Sensing of Environment* 141 (2014): 105-115.

Libbrecht, K. G. (2005). The physics of snow crystals. Reports on Progress in Physics, 68(4), 855-895.

Sturm, M., Holmgren, J., & Liston, G. E. (2010). A seasonal snow cover classification system for local to global applications. Journal of Climate, 24(20), 5305-5316.

Harpold, A. A., Molotch, N. P., Musselman, K. N., Bales, R. C., Kirchner, P. B., Litvak, M., ... & Brooks, P. D. (2017). Laser vision: lidar as a transformative tool to advance critical zone science. Hydrology and Earth System Sciences, 21(1), 1983-2001.

Raleigh, M. S., Lundquist, J. D., & Clark, M. P. (2015). Exploring the impact of forcing error characteristics on physically based snow simulations within a global sensitivity analysis framework. Water Resources Research, 51(11), 9057-9073.

Barnett, T. P., Adam, J. C., & Lettenmaier, D. P. (2005). Potential impacts of a warming climate on water availability in snow-dominated regions. Nature, 438(7066), 303-309.

Leisenring, M., & Moradkhani, H. (2011). Snow water equivalent prediction using bayesian data assimilation methods. Stochastic Environmental Research and Risk Assessment, 25(2), 253-270. doi:https://doi.org/10.1007/s00477-010-0445-5

Sarhadi, A., Kelly, R. and Modarres, R. (2014), A. SARHADI, R. KELLY AND R. MODARRES. Hydrol. Process., 28: 4640-4653. https://doi.org/10.1002/hyp.10184

Brown, R. D., Brasnett, B., & Robinson, D. (2003). Gridded North American monthly snow depth and snow water equivalent for GCM evaluation. Atmosphere-Ocean, 41(1), 1–14. https://doi.org/10.3137/ao.410101

Marks, D., and J. Dozier (1992), Climate and energy exchange at the snow surface in the Alpine Region of the Sierra Nevada: 2. Snow cover energy balance, Water Resour. Res., 28(11), 3043–3054, doi:10.1029/92WR01483.

Zhang, J., Pohjola, V. A., Pettersson, R., Norell, B., Marchand, W. D., Clemenzi, I., & Gustafsson, D. (2021). Improving the snowpack monitoring in the mountainous areas of Sweden from space: a machine learning approach. Environmental Research Letters, 16(8), 084007.

Diks, C. G., & Vrugt, J. A. (2010). Comparison of point forecast accuracy of model averaging methods in hydrologic applications. Stochastic Environmental Research and Risk Assessment, 24, 809-820.