Monitoring Snow Water Equivalent (SWE) Using MODIS Time-Series Data and Machine Learning in Turnagain Arm, Alaska

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Abstract

Global warming and water scarcity have made snowfall an essential area of study. Rapid melting of glaciers and snowfields transforms ecosystems and water availability, emphasizing the need to measure snow water equivalent (SWE). This study employs SWE, the Normalized Difference Snow Index (NDSI), and Snow Depth from MODIS time-series images to monitor and analyze snow-related changes effectively. MODIS images, with their consistent temporal resolution, are ideal for tracking seasonal and annual snow variations. This research examines MODIS data spanning 2007 to 2023 during the winter months (December to March) to evaluate changes in snow-covered areas and their water equivalents. The study focuses on Turnagain Arm, a prominent waterway in the north-western Gulf of Alaska. Machine Learning methods were applied to model SWE variations, using NDSI and Snow Depth as predictors. A test-train split approach was implemented to ensure robust and reliable results. Data from six USDA monitoring stations around Turnagain Arm supported the model's accuracy and relevance. The findings reveal significant trends in snow coverage and water storage over time, providing valuable insights for understanding snowmelt dynamics and informing strategies for water resource management in the region. This comprehensive approach demonstrates the potential of integrating remote sensing data and Machine Learning techniques to monitor environmental changes caused by global warming.

1. Introduction

More than 30 percent of the Earth is covered by seasonal snow, and about 10 percent by permanent glaciers. The melting of glaciers is a well-documented effect of global warming. As the climate warms, Earth's glaciers are melting at an accelerating rate. The Portage Glacier, located in the U.S. state of Alaska, is the headwater of the Turnagain Arm, one of two narrow branches at the north end of Cook Inlet. Turnagain Arm is subject to climate extremes and large tide ranges.
The glaciers have been retreating for over a century due to warmer temperatures and changes in precipitation. Since 1900, the terminus has retreated as much as 12 km (7.5 mi). Snow water equivalent (SWE) is the amount of water contained within the snowpack. It is defined as the depth of water that would result if the entire snowpack were melted instantaneously. SWE is typically measured in millimeters or inches. It is an important parameter for hydrological and meteorological studies, as it provides information on the amount of water that will be available for runoff during the spring melt.
A quantitative understanding of snow thickness and snow water equivalent (SWE) on glaciers is essential to a wide range of scientific and resource management topics. However, robust SWE estimates are observationally challenging, in part because SWE can vary abruptly over short distances in complex terrain due to interactions between topography and meteorological processes. McGrath et al. found that SWE can be highly variable (40% difference) over short spatial scales (tens to hundreds of meters), especially in the ablation zone where the underlying ice surfaces are typically rough.
Additionally, recent studies have shown that climate change has led to shifts in snowfall patterns, with some regions experiencing increased snowfall while others face prolonged drought conditions. These variations further complicate the accurate estimation of SWE, necessitating the use of advanced remote sensing techniques. The integration of satellite imagery with in-situ observations helps to improve the reliability of SWE measurements and allows for large-scale monitoring of snowpack dynamics.
As both the model predictions and passive microwave snow water equivalent (SWE) observations contain large errors attributable to land surface complexities and temporally frequent snowmelt processes in the western United States, the 500-m daily Moderate Resolution Imaging Spectroradiometer (MODIS) snow cover area (SCA) product has been widely used as an important constraint on snowpack processes in land surface and hydrological models. MODIS provides consistent spatial coverage, making it an invaluable tool for tracking changes in snow distribution over time.
For calculating SWE from the NDSI index from MODIS satellite images, the best months are December to March, which represent the winter season in the USA. These months record the highest snowfall accumulation, making them ideal for studying snowpack dynamics. The seasonal cycle of snow accumulation and melt plays a crucial role in regional hydrology, affecting river flow, reservoir storage, and water availability for agriculture and human consumption.
For monitoring SWE changes, a long-term dataset is necessary to capture interannual variability and detect significant trends. This study utilizes MODIS images spanning 18 years, from 2005 to 2023, focusing on the winter months (December to March). By analyzing this extensive dataset, we aim to enhance our understanding of snowpack evolution and its implications for water resource management in a changing climate.
Monitoring and analyzing snow variations play a crucial role in hydrological studies, climate research, and water resource forecasting. Snow Water Equivalent (SWE) is a key parameter that represents the amount of water stored in snow. This parameter can be obtained through ground-based measurements or estimated using statistical models based on related variables

such as the Normalized Difference Snow Index (NDSI) and snow depth. This study employs polynomial Regression to model the relationship between SWE, NDSI, and snow depth.

2. Proposed Method

2.1 Flowchart

The flowchart below outlines the key steps in the Snow Water Equivalent (SWE) estimation research process. It begins with data acquisition from MODIS imagery, incorporating SWE, the Normalized Difference Snow Index (NDSI), and Snow Depth. The data is then pre-processed through cleaning, normalization, and test-train splitting to ensure model accuracy. A polynomial regression model is applied to predict SWE using NDSI and Snow Depth as input variables, followed by model evaluation using metrics such as Mean Absolute Error (MAE), Mean Squared Error (MSE), and the R^2-score. The results are analyzed to identify trends in snow cover variability and their implications for water resources. The study concludes with insights into climate change impacts and future water management strategies.

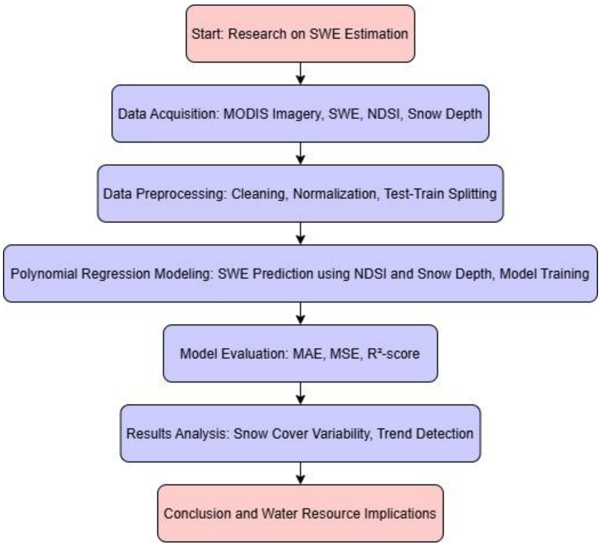


Figure 1. The flowchart of the proposed methodology

2.2 Data

The NDSI is defined as the difference of reflectance observed in a visible band such as MODIS band 4 (0.555 Am) and a short-wave infrared band such as MODIS band 6 (1.640 Am) divided by the sum of the two reflectances:

$$NDSI = \frac{(B4 - B6)}{(B4 + B6)} \quad (1)$$

where, *NDSI* = The Normalized Difference Snow Index, B4 = very high visible (VIS) reflectance, and B6 = very low reflectance in the shortwave infrared (SWIR).

The MODIS imagery which is used is the MOD10A1 V6. It is a Snow Cover Daily Global 500m product that contains snow cover, snow albedo, fractional snow cover, and quality assessment (QA) data. Snow cover data are based on a snow mapping algorithm that employs a Normalized Difference Snow Index (NDSI) and other criteria tests. The period of monitoring NDSI from MOD10A1 V6 images is December 2005 to February 2023 and just for four months, during which the winter season (December to March) has more snow and snow water equivalent. Also, Snow Water Equivalent (SWE) which drives from ground-based stations represents the amount of liquid water contained within a snowpack. It is a crucial parameter for hydrological and climate studies, as it directly affects water resource management and runoff estimation. The SWE is calculated using the following equation:

$$SWE = \rho_s \times Hs \quad (2)$$

where SWE is the snow water equivalent (mm or cm), ρ is the snow density (kg/m³), and Hs is the snow depth (mm or cm).

Snow Density Considerations: Fresh snowfall has a low density, typically between 50 and 150 kg/m³. Compacted or older snow has a higher density, often ranging from 200 to 400 kg/m³. Wet snow can have densities exceeding 500 kg/m³.

To obtain accurate SWE values, precise measurements of both snow depth (Hs) and snow density **(ρ)** are required. If snow density is unknown, empirical relationships or remote sensing techniques, such as the Normalized Difference Snow Index (NDSI), can be used to estimate it.

2.3 Location

Station Name	Station ID	Coordinates
Anchorage Hillside	1070	61.11, -149.67
Indian Pass	946	61.07, -149.45
Mt. Ayesha	1103	60.96, -149.09
Turnagain Pass	954	60.78, -149.18
Grand View	956	60.61, -149.06
Summit Creek	955	60.62, -149.53

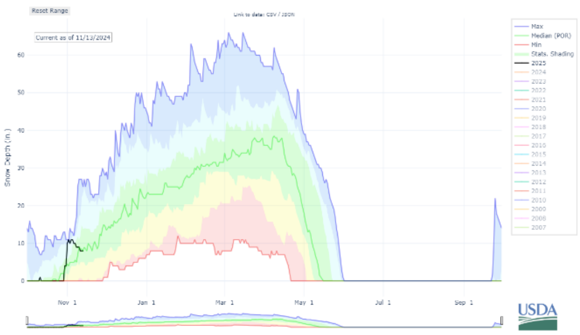
Table 1. Information on ground stations

Table 1 illustrates six ground stations that are measuring Snow Water Equivalent from 2005 to 2023 and they are located around the Turnagain Arm. In the picture below there are the locations of ground stations and Turnagain Arm in map from USDA.

Figure 2. SWE measuring from ground stations map

2.4 SWE and Snow Depth Figures

The following figures present the variations in Snow Water Equivalent (SWE) and snow depth for each of the six monitoring stations over 18 years. These visualizations provide a comprehensive representation of temporal trends in snow accumulation and water content. The data used to generate these figures were obtained from the United States Department of Agriculture (USDA) database, ensuring accuracy and consistency in the recorded measurements. Each station's dataset highlights seasonal and interannual variations, offering valuable insights into long-term snow dynamics and the potential impacts of climate change on snowpack stability.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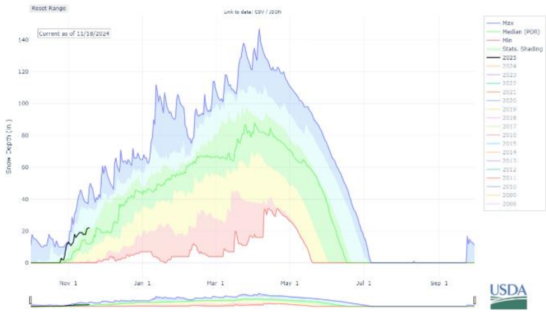
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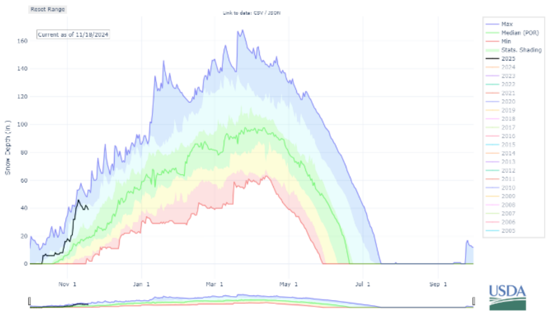
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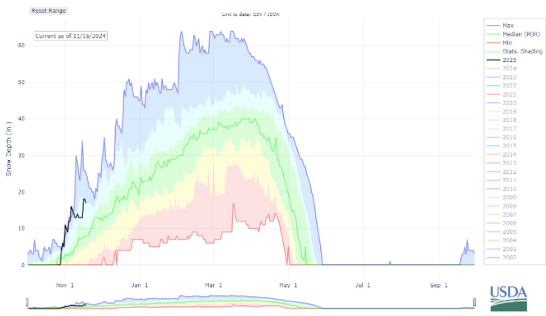
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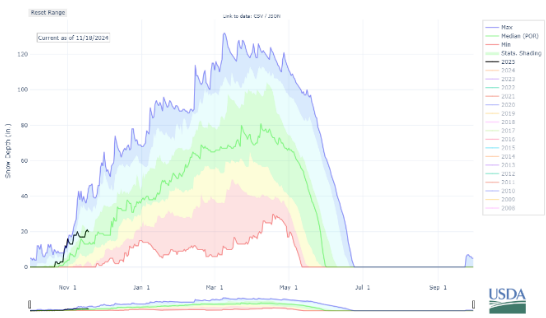
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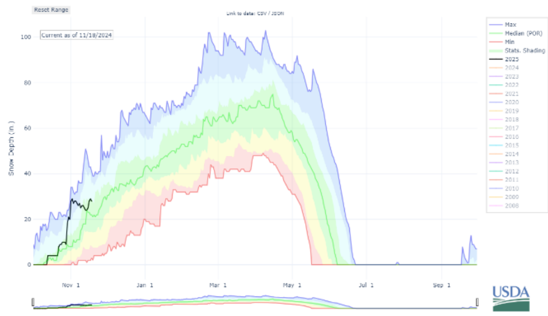
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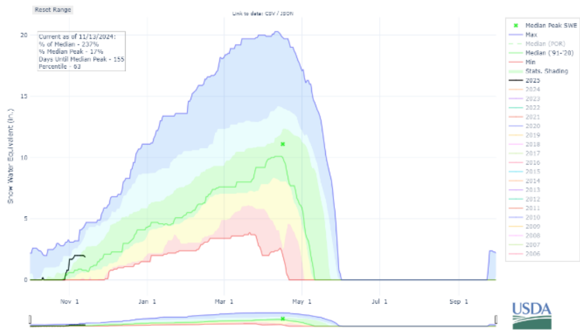
Figure 3. Snow Depth Index in (a) Anchorage Hillside station, (b) Grandview station, (c) Turnagain_pass station, (d) Summit Creek station, (e) Mt.Alyeska station, (f) Indian_pass station.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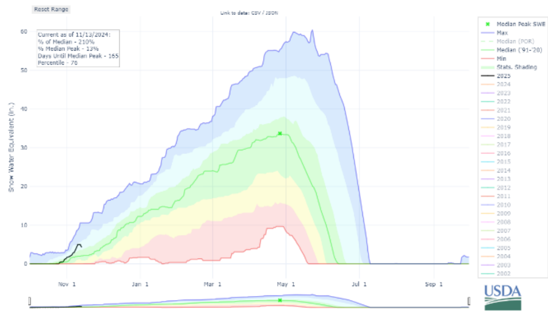
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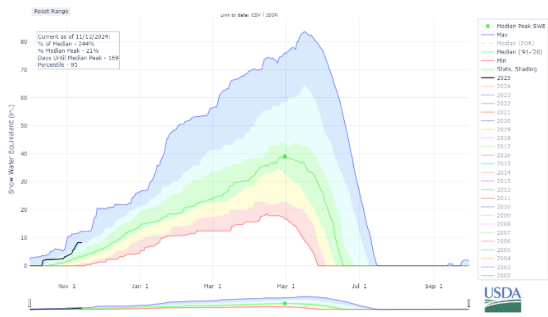
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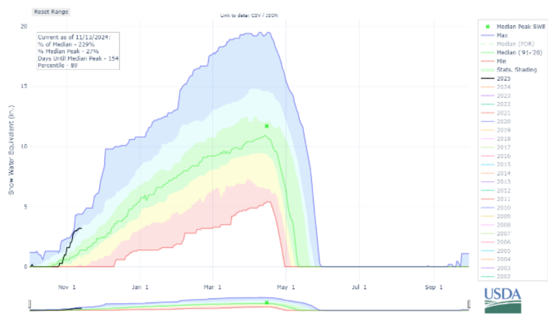
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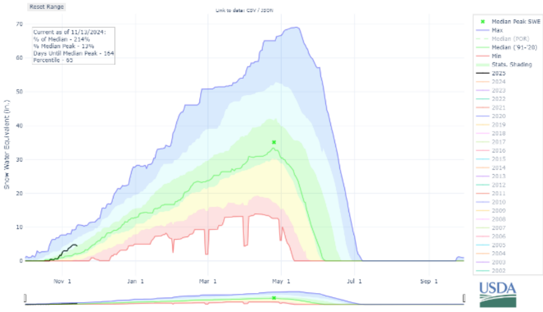

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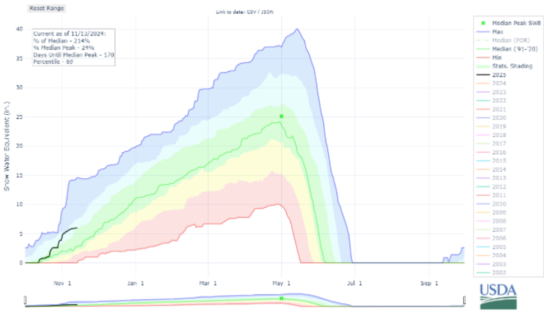

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Figure 4. SWE in (a) Anchorage Hillside station, (b) Grandview station, (c) Turnagain_pass station, (d) Summit Creek station, (e) Mt.Alyeska station, (f) Indian_pass station.

Figure 5 presents the temporal variations of Snow Water Equivalent (SWE) as measured and the Normalized Difference Snow Index (NDSI) derived from six monitoring stations over the period from December 2005 to March 2023. A comparative assessment of these datasets reveals an inverse relationship between the snow cover index and the snow water equivalent index. Specifically, in regions experiencing seasonal temperature increases, particularly during warmer months, accelerated snowmelt leads to a reduction in snow cover. This phenomenon is reflected in decreasing NDSI values, signifying diminished snow coverage, while simultaneously, SWE measurements from ground stations exhibit an increase due to the additional water content derived from melting snow. This inverse correlation underscores the influence of temperature fluctuations on snowpack dynamics, wherein elevated temperatures contribute to the depletion of snow cover while augmenting the measurable water equivalent from melted snow.

2.4 Methodology

We employ polynomial regression to model the relationship between snow water equivalent (SWE), normalized difference snow index (NDSI), and snow depth. The dataset consists of SWE measurements recorded at the Anchorage Hillside ground station, along with corresponding NDSI values derived from satellite imagery and snow depth records.
To improve model accuracy and mitigate overfitting, the dataset is divided into two subsets: training data, comprising 80 percent of the total observations, is used for model training, while the remaining 20 percent serves as test data for model evaluation.
The modeling approach involves the application of polynomial regression to establish the relationship between SWE and the two independent variables, NDSI and snow depth. Initially, input features are expanded to a third-degree polynomial using polynomial feature transformation. Subsequently, a linear regression model is fitted to the transformed dataset.
The performance of the model is evaluated using three statistical metrics: mean absolute error (MAE), mean squared error (MSE), and the coefficient of determination (R^2-score). The model outputs include the polynomial regression coefficients and the intercept, which indicate the influence of independent variables on SWE prediction. The R^2-score serves as a key indicator of the model's goodness of fit and predictive accuracy.

Station Name	MAE	MSE	R^2-score
Anchorage Hillside	0.73	0.92	0.94
Indian Pass	2.77	13.85	0.86
Mt. Ayesha	1.15	2.14	0.86
Turnagain Pass	1.27	2.55	0.91
Grand View	1.07	1.51	0.83
Summit Creek	2.01	7.06	0.93

Table 2. Information on statistical metrics

The results indicate that third-degree polynomial regression effectively captures the relationship between SWE, NDSI, and snow depth. This approach can be a valuable tool for SWE estimation, particularly in regions where ground-based measurements are limited.

3. Conclusion

This study underscores the profound impact of climate change on snow dynamics and water resource availability, particularly in Turnagain Arm, a vital waterway situated in the northwestern Gulf of Alaska. The rapid melting of glaciers and snow-covered regions, driven by increasing temperatures, highlights the urgent need for continuous monitoring and precise measurement of Snow Water Equivalent (SWE). As temperatures continue to rise, these shifts in snowpack behavior have significant long-term implications for hydrology, freshwater availability, and regional climate patterns. Given the escalating rate of snowmelt, it is critical to develop reliable methods for quantifying these changes, allowing for better prediction and management of water resources that rely on seasonal snowpack.
To track these changes effectively, this research leverages MODIS time series imagery spanning from December 2005 to March 2023. By using high-temporal resolution satellite data, the study provides an extensive examination of both seasonal and interannual variations in snow accumulation and water content. A focus on the winter months—when snow coverage is at its peak—ensures that the analysis captures critical data on snowpack dynamics. By concentrating on these months, the study successfully illustrates the varying behavior of snow packs, reflecting shifts in snow depth, melt timing, and the subsequent impact on hydrological cycles and regional water systems. This methodology offers essential insights into how snow accumulation patterns change over time and how they can be influenced by broader climate shifts.
To further refine the analysis, polynomial regression is applied to model the relationship between SWE, the Normalized Difference Snow Index (NDSI), and snow depth. The dataset includes SWE measurements recorded at the Anchorage Hillside ground station, alongside NDSI values derived from satellite imagery and recorded snow depth. This approach is particularly advantageous as it allows for the incorporation of non-linear relationships between the variables, which are often present in environmental systems. The regression model begins by transforming the input features into a third-degree polynomial, enhancing the ability of the model to capture complex interactions between the independent variables. A linear regression model is then fitted to the transformed data, enabling the estimation of SWE based on the relationships between NDSI, snow depth, and SWE.
The results of this modeling approach provide significant insights into the relationship between SWE, snow depth, and NDSI, with third-degree polynomial regression proving to be an effective

tool for capturing the complexities of snow dynamics. The model's performance is assessed through several evaluation metrics, with the regression coefficients and intercept providing valuable information on the individual contributions of NDSI and snow depth to SWE predictions. Additionally, the R^2-score further validates the robustness of this approach. The relatively high R^2-score indicates that the model is capable of explaining a substantial proportion of the variability in SWE, making it a reliable method for estimating SWE in similar regions and conditions.

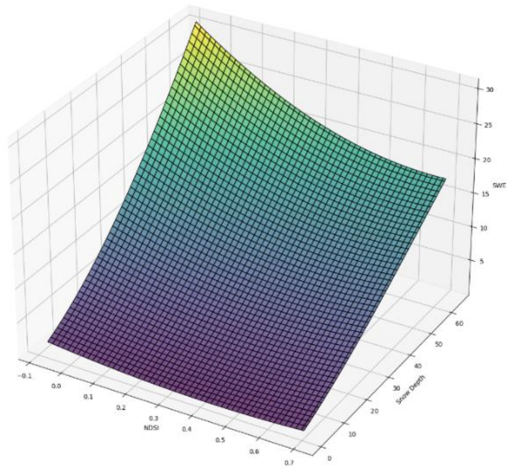
The integration of snow depth derived from NDSI and the measured SWE has revealed an important trend: an inverse relationship between snow cover and SWE. This relationship demonstrates that as snow-covered areas decrease, SWE increases due to the heightened water content in the melting snow. These trends align with broader patterns observed in other regions affected by climate change, where warming temperatures contribute to reduced snow accumulation and an earlier onset of snowmelt. As a result, the available snowpack water is released more rapidly, further exacerbating changes in water availability and contributing to altered runoff patterns. These findings have profound implications for water resource management, as they directly impact the availability of freshwater, ecological systems, and local and regional climates. This inverse relationship between snow cover and SWE is a crucial factor for understanding future water resource availability in regions highly dependent on snowpack for water storage and runoff.

The study not only highlights these important trends but also provides a structured and user-friendly methodology for SWE estimation in areas where ground-based measurements are scarce or unavailable. By offering a reliable framework for integrating satellite-derived NDSI data and ground-based snow depth measurements, this research contributes to improving snow estimation techniques. It is particularly valuable for regions where ground station data is limited, allowing for more comprehensive and accurate monitoring of snowpack dynamics. These findings emphasize the necessity of continuous monitoring to enhance our understanding of snow dynamics and adapt to climate change more effectively. The results presented in this study contribute to a broader understanding of how snowpack and water resources are shifting in response to climate change, underscoring the need for enhanced strategies to manage water resources and ensure sustainability in a warming world.

Ultimately, this research provides critical insights into the evolving behavior of snow packs and their implications for hydrological processes, resource management, and ecological systems. The findings will support more informed decision-making in water resource management, climate adaptation planning, and the development of strategies for mitigating the impacts of climate change on snow-dependent water systems. The ability to predict and monitor these changes will be crucial for developing adaptive solutions that can address the challenges posed by a warming climate and ensure the availability of water resources for future generations. In **Figure 5**, the variations in SWE, the NDSI, and Snow Depth are depicted for six monitoring stations, covering the period from 2005 to 2023. These visualizations provide an in-depth understanding of the trends observed in snow cover and water storage dynamics over time.

The 3D polynomial regression plot illustrates the relationship between SWE, NDSI, and Snow Depth. This visualization helps in identifying complex interactions between these variables, emphasizing the impact of climate change on snowpack variations. The polynomial regression model enables effective SWE estimation by incorporating satellite-derived NDSI values and measured Snow Depth, ensuring a comprehensive analysis of snow distribution.

By analyzing the data from different stations across multiple years, this study aims to capture interannual variations and long-term trends in snow accumulation and melting patterns. These insights contribute to a better understanding of hydrological processes and their implications for water resource management, ecological stability, and climate adaptation strategies. The ability to predict and monitor these changes will be crucial for developing adaptive solutions to mitigate the impacts of climate change on snow-dependent water systems and ensure sustainable water availability for future generations.



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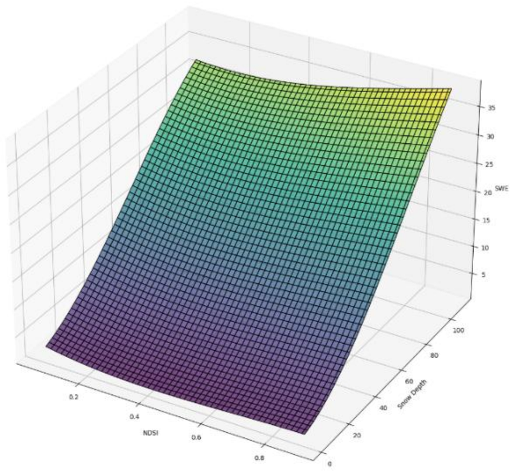

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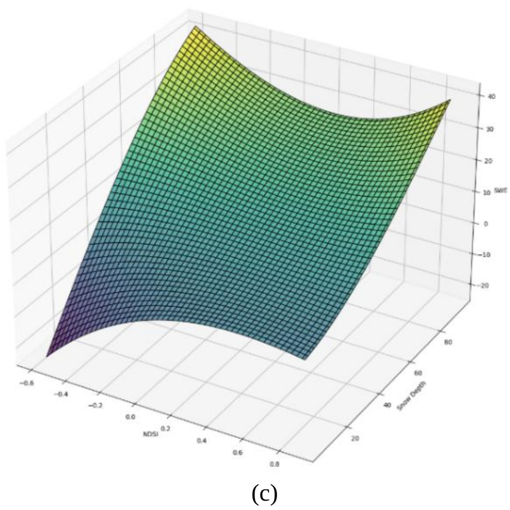

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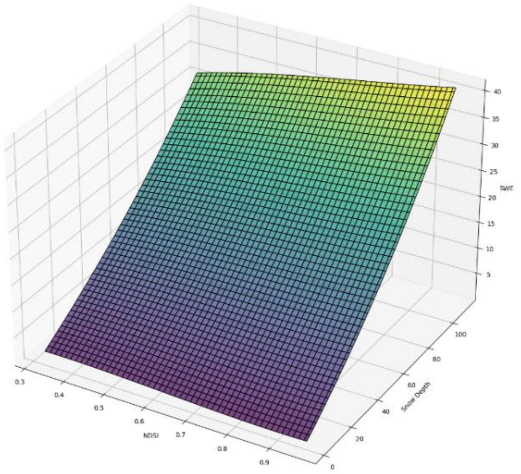

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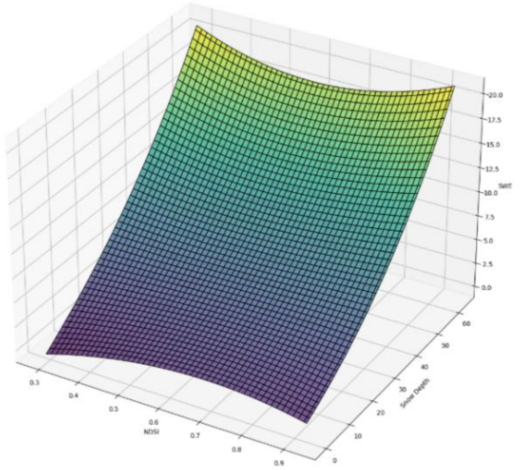

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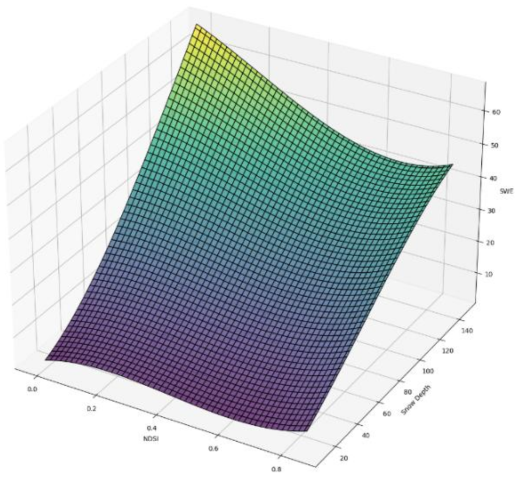

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Figure 5. The 3D plot in (a) Summit-Creek station, (b) Indian_pass station, (c) Mt.Alyeska station, (d) Turnagain_pass station, (e) Grandview station, (f) Anchorage Hillside station.

The plot in **Figure 6**. presents the relationship between actual SWE values and the predicted SWE obtained through a second-degree polynomial regression model. The red dashed line represents the ideal 1:1 relationship, where perfect predictions would align. The proximity of data points to this line indicates the model's accuracy in estimating SWE. A strong alignment suggests a reliable predictive performance, while deviations highlight potential sources of error, such as variations in snow properties or limitations in input data.

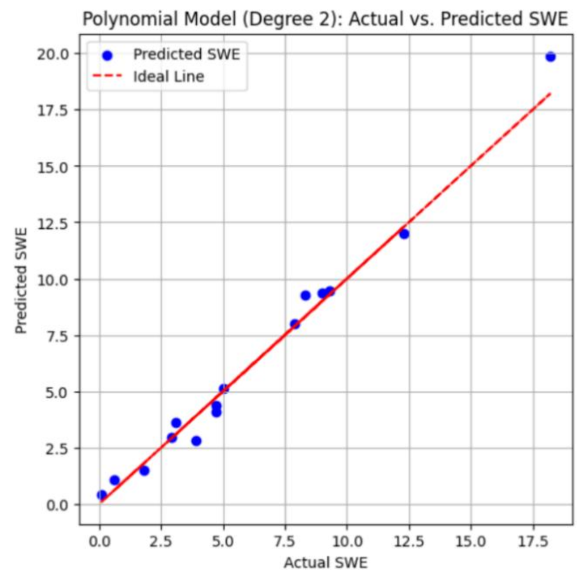

Figure 6. The scatter plot of actual vs predicted SWE

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