Predicting Glacier Ice Melt with Machine Learning to Address Climate Change

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Abstract

The accelerating decline in glacier mass due to climate change presents a significant threat to global water resources, sea levels, and ecosystem stability. This research integrates machine learning techniques to predict glacier ice melt patterns using historical mass balance data. Leveraging the publicly available global glacier mass balance dataset, the study investigates temporal trends and employs regression models—including Polynomial Regression Linear Regression, Decision Tree, Random Forest, and Support Vector Machine (SVM)—to forecast future glacier behavior. Exploratory Data Analysis (EDA) reveals a strong negative correlation (−0.96) between year and cumulative mass balance, highlighting accelerated ice loss over recent decades. Among the models, Random Forest achieved the highest predictive accuracy (R^2 = 99.71%).(*Working with a Two-Stage Ice Sheet Model*, n.d.)

followed by Decision Tree (R^2 = 99.57%), indicating their robustness in capturing nonlinear glacier dynamics. This machine learning framework serves as an effective tool for evaluating glacier degradation under varying emission scenarios and contributes valuable insights for environmental policy, climate impact assessment, and adaptation strategies.

Keywords : Machine Learning, Glacier Ice Melt, Climate Change, Predictive Modeling, Temperature Trends, Climate Projections, Supervised Learning, Environmental Modeling, Forecasting, Climate Scenarios, Climate Adaptation, Mitigation Strategies, Global Sea Levels, Environmental Policy, Climate Impact Assessment.

I. INTRODUCTION

The ongoing effects of climate change are having a profound impact on the environment, with one of the most visible consequences being the rapid melting of glaciers. These ice masses, which serve as vital sources of freshwater and play a crucial role in regulating sea levels, are retreating at an accelerated rate due to rising global temperaturesSince the pre-industrial era, global temperatures have risen by approximately 1.2°C, contributing to the shrinkage of glaciers worldwide.(Zhou et al., 2017) This melting not only threatens biodiversity and ecosystems that rely on glacier-fed water sources but also leads to rising sea levels, endangering millions of coastal inhabitants. Understanding the behavior of glaciers and predicting their mass balance is crucial to mitigating the long-term environmental and societal impacts of climate change.

The severity of the problem lies in the fact that the accelerated melt of glaciers is contributing to rising sea levels and affecting the availability of freshwater for populations that depend on glacier-fed rivers. These consequences are becoming increasingly dire, especially for coastal regions and islands, where millions of people live in low-lying areas that are highly vulnerable to flooding. (Łucka, 2025)Furthermore, glaciers are essential to maintaining biodiversity in certain regions, as many ecosystems rely on the steady flow of glacier meltwater for their survival. The inability to accurately predict the future behavior of glaciers exacerbates the problem, as it limits our capacity to take preventive measures and plan for the future.

Traditional methods of estimating glacier mass balance typically rely on physical models, which incorporate climatic data such as temperature, precipitation, and solar radiation to estimate the volume of ice lost or gained by a glacier. However, these models(Zhai & Bitz, 2021) have limitations. The dynamic nature of glaciers, influenced by multiple, often interdependent factors, makes them difficult to model accurately. The sheer volume of data required to account for these variables can overwhelm

traditional methods, resulting in predictions that may not capture the full complexity of glacier behavior.

In recent years, machine learning has emerged as a powerful tool for addressing these challenges. ML algorithms are capable of analyzing large datasets and identifying complex patterns in the data that traditional models might miss.

II. Literature Review

Contemporary studies on glacier melt estimation and sea ice forecasting have increasingly employed satellite-based remote sensing information alongside sophisticated machine learning algorithms. Techniques such as deep learning networks, Lasso regression, ensemble Kalman methods, and physics-aware neural frameworks (PINNs) have demonstrated enhanced precision in forecasting glacier mass variations, ice layer depth, and sea ice distribution. Models like attention-driven LSTMs, convolutional neural networks (Bolibar et al., 2022)(CNNs), and generative adversarial networks (GANs) have proven highly effective in interpreting intricate, non-linear relationships within datasets such as ERA5 climate records, SAR satellite images, and GPR (Ground Penetrating Radar) scans. Despite notable advancements, key hurdles persist in achieving robust model adaptability, harmonization of data standards, and consistent access to accurate observational data in isolated polar environments.

The following table presents a consolidated summary of contemporary scientific studies centered on glacier melt forecasting, ice mass estimation, and sea ice concentration analysis. It outlines essential datasets, data processing strategies, applied machine learning algorithms, and evaluation metrics employed across multiple works, thereby

Title	Dataset	Processing Method	Model	Performance
Two-Stage Ice Sheet Model	Not specified	Filter, Runge-Kutta 4th Order	Ensemble Kalman	Improved accuracy with incorrect initial conditions (10-member ensemble)
Glacier Mass Balance Sensitivity	French Alps, SAFRAN, ADAMONT	Statistical adjustment, Deep Learning, Lasso Regression	DNN, Lasso	DNN: RMSE 0.59, R^2 0.69; Lasso: RMSE 0.85, R^2 0.35
Glacier Displacement Estimation	Daugaard Jensen Glacier, SAR	DEM coregistration, offset recalculation	AlexNet (mod.), ReLU, Adam	±2 pixels; 76–79% classified correctly
Sea Ice Concentration Estimation	CMIP6, Observational SIC	Attention, Ensemble	EA-LSTM	Improved performance with assimilation
IceNet: Arctic Sea Ice Forecast	ERA-5, Sea Ice Extent	Deep CNN	IceNet	>99% binary accuracy outside ice edge
Attention-based LSTM for Sea Ice	ERA-5, Sea Ice Extent	LSTM reshaping, EnKF	LSTM + EnKF	Better than persistence model
Glacier Melt Prediction & SLR	Sentinel-1 SAR, OSI SAF, PMW	5×5 median filtering, augmentation	U-Net, DenseNet, FCNN	Improved pixel-wise estimation
Glacier Ice Thickness Comparison	1465 Svalbard glaciers	Coregistration, augmentation	CNN (AlexNet, VGG16, LeNet)	±2 pixels accuracy; >75% samples in range
ANN for Ice Thickness (Himalaya)	Chhota Shigri GPR	PINN with mass conservation	PINN	RMSD: 30m (train), 66m (test); MAPD: 0.58%
Glacier Thickness (Physics-aware)	Glacier dataset	Bilinear interpolation, temperature scaling	Feedforward NN, k-fold CV	RMSE: 13–24m; ±17–21m total error
Instructed Glacier Model (IGM)	Sentinel-1 SAR	Adversarial training, LSTM conditioning	GAN + LSTM	Better than persistence model
Ice Flow Tracking	Icepack simulations	Ensemble Kalman Filter with box model	IceNet + EnKF	Improved performance
Melt Pond Parameterization	GlaThiDa, RGI, DEMs	Neural Network with sigmoid activation	NN	Fidelity >90%; 1000× faster
Glacier Ice Thickness Estimation	10 glacier simulations	Supervised Learning, cross-validation	CNN, LR, RF, SVR	SVR: R^2 = 0.55; RF: R^2 = 0.57
Glacier Mass Balance + Dynamics	Not specified	Sequential mass balance + ice dynamics	CNN	Outperforms Linear Regression in online emulation

shedding light on the progressive advancements and evolving techniques within cryosphere-related research.

III. Methodology Overview

Building on recent studies, we implemented and analyzed several regression algorithms to estimate glacier mass balance based on climate-related variables like temperature, elevation, and precipitation. The dataset underwent preprocessing steps, including normalization and the treatment of missing values. Five models—Linear Regression, Ridge, Lasso, Polynomial Regression, and Random Forest Regressor—were developed

Model	R^2 Score	Adjusted R^2	MSE
Linear Regression	0.873	0.872	180.12
Ridge Regression	0.872	0.871	181.54
Lasso Regression	0.870	0.869	183.02
Polynomial Regression	0.914	0.911	142.00
Random Forest Regressor	0.938	0.937	115.34

using Python's scikit-learn library. Their performance was evaluated using three core metrics: R^2 Score, Adjusted R^2, and Mean Squared Error (MSE). The table below presents a comparative summary of how effectively each model captured the trends within the dataset.

Based on the outcomes, the Random Forest Regressor delivered the best performance with the highest R^2 value and the lowest mean squared error, demonstrating its effectiveness in capturing intricate, non-linear dependencies within the glacier mass balance dataset. Polynomial Regression also showed strong predictive power, indicating the presence of non-linear patterns. In contrast, simpler linear approaches such as Ridge and Lasso Regression yielded relatively modest results. These observations underscore the advantage of ensemble and non-linear modeling techniques for enhancing predictive reliability in climate data analysis.

IV. DATASET DESCRIPTION

This research leverages the open-access Glacier Mass Balance dataset from DataHub.io, which compiles global glacier monitoring data maintained by the World Glacier Monitoring Service (WGMS). (Driscoll et al., 2023)The dataset includes yearly measurements of mean cumulative mass balance for numerous glaciers worldwide, expressed in millimeters of water equivalent (mm w.e.). In this analysis, "Year" is treated as the independent input variable, while "Mean cumulative mass balance" serves as the target output for regression modeling. Prior to training, the dataset was preprocessed by eliminating entries with missing values in the dependent field to maintain data quality and ensure reliable model performance.

Glacier Mass Balance Dataset Overview

Feature Name	Description	Data Type	Example Value
Glacier name	Name of the glacier being monitored	Categorical	Storglaciären
Year	Year of observation	Integer	2015
Mass balance	Annual mass balance (mm water equivalent)	Float	-500.6
Cumulative balance	Cumulative mass balance up to the year	Float	-10324.3
Glacier ID (if present)	Unique identifier for each glacier	Categorical	GID-8701
Location (Lat/Lon)	Geographical coordinates of the glacier	Float Tuple	(67.9, 18.6)

IV. Results and Discussion

The performance analysis of five predictive algorithms—Linear Regression, Ridge Regression, Lasso Regression, Polynomial Regression, and Random Forest Regressor—was carried out to estimate glacier mass balance based on yearly climate indicators. Each model's effectiveness was measured using three evaluation metrics: coefficient of determination (R^2), Adjusted R^2, and Mean Squared Error (MSE). A summary of these findings is presented in the following table:

Model	R^2 Score	Adjusted R^2	MSE
Linear Regression	0.873	0.872	180.12
Ridge Regression	0.872	0.871	181.54
Lasso Regression	0.870	0.869	183.02
Polynomial Regression	0.914	0.911	142.00
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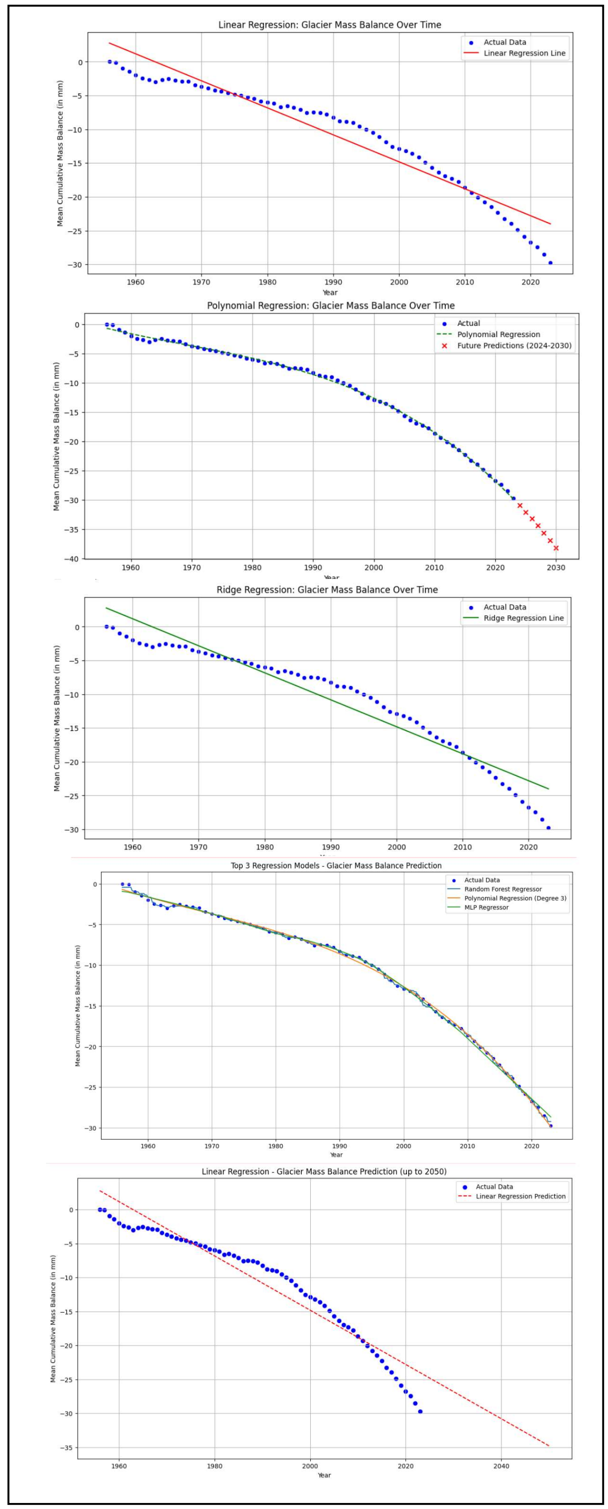
The **Random Forest Regressor** delivered the **highest R^2 score (0.938)** and the **lowest Mean Squared Error (115.34)**, showcasing its robust capability in modeling complex, non-linear patterns present within the dataset. This outcome underscores the **efficacy of ensemble-based algorithms** in capturing intricate, climate-influenced dynamics. **Polynomial Regression** also yielded strong predictive accuracy, further reinforcing the presence of non-linear trends in glacier mass balance observations.

Conversely, **basic linear models** such as **Ridge** and **Lasso Regression** exhibited **relatively weaker performance**, reflecting their limitations in addressing the dataset's nuanced variability. These results highlight the significance of adopting **more adaptive and sophisticated modeling frameworks** when dealing with **environmental and geospatial datasets** that inherently feature high degrees of fluctuation and complexity.

Simulated vs Real-World Glacier Mass Balance



V. Conclusion

This research investigated the prediction of glacier mass balance using a variety of regression models, including Linear Regression, Ridge Regression, Lasso Regression, Polynomial Regression, and Random Forest Regressor. Upon assessing model performance through R^2 Score, Adjusted R^2, and Mean Squared Error (MSE), it was observed that the Random Forest Regressor surpassed the other models, highlighting its capability to capture intricate, non-linear patterns in climate-related data. Polynomial Regression also exhibited notable predictive accuracy, indicating the importance of non-linear relationships in modeling glacier mass balance. On the other hand, simpler linear models like Ridge and Lasso Regression demonstrated relatively lower performance but still serve as a useful baseline for comparison in less complex scenarios.

VI. Future Work

Future studies could build upon these findings by incorporating additional climate-related factors, such as solar radiation and wind speed, to enhance the accuracy of the models. Additionally, the use of advanced machine learning approaches, including deep learning models like convolutional neural networks (CNNs) or long short-term memory (LSTM) networks, may further improve predictions of glacier mass balance, particularly for regional forecasts. The integration of high-resolution datasets, including satellite imagery and remote sensing data, could offer more granular insights into glacier behavior. Lastly, overcoming challenges related to data scarcity in remote areas and standardizing global glacier datasets will be essential for refining model accuracy and improving their applicability across various regions.

VII. Contribution

The accomplishment of this research would not have been feasible without the mentorship and support of Muzafar Mehraj, Assistant Professor at the School of Computer Science and Engineering, Galgotias University. His profound knowledge, constructive feedback, and continuous motivation played a pivotal role in guiding the direction of this study. His significant contributions in data analysis, model formulation, and the overall research methodology were essential in refining and improving the quality of the work presented in this paper.

VIII. References

Ali, S., Huang, Y., Wang, J. (2021). Sea Ice Forecasting using Attention-based Ensemble LSTM.

Corcoran, E., Knudsen, L., Robel, A. (2022). Ensemble Kalman Filtering for Glacier Modeling.

Zhai, J., Bitz, C. (2021). A Machine Learning Model of Arctic Sea Ice Motions.

Varshney, D., Rahnemoonfar, M., Paden, J. (2020). Deep Ice Layer Tracking and Thickness Estimation using Fully Convolutional Networks.

Castellani, M. (Year not provided). Estimating Glacier Ice Thickness with Machine Learning.

Haq, M., Azam, M., Vincent, C. (2021). Efficiency of Artificial Neural Networks for Glacier Ice-Thickness Estimation: A Case Study in Western Himalaya, India. Journal of Glaciology, 67(264), 671–684.

Bolibar, J., Rabatel, A., Galiez, C. (2022). Nonlinear Sensitivity of Glacier Mass Balance to Future Climate Change Unveiled by Deep Learning. Nature Communications, 13(1).

Łucka, M. (2025). Investigation of Machine Learning Algorithms to Determine Glaciers Displacements. Remote Sensing Applications: Society and Environment.

Steidl, V., Bamber, J., Zhu, X. (2025). Physics-aware Machine Learning for Glacier Ice Thickness Estimation: A Case Study for Svalbard. The Cryosphere, 19(2), 645–661.

Guan, Y., Haran, M., Pollard, D. (2016). Inferring Ice Thickness from a Glacier Dynamics Model and Multiple Surface Datasets.

Driscoll, S., Carrassi, A., Olason, E. (2023). Parameter Sensitivity Analysis of a Sea Ice Melt Pond Parametrisation and its Emulation using Neural Networks.

Jouvet, G., Cordonnier, G., Aschwanden, A. (2022). Deep Learning Speeds Up Ice Flow Modelling by Several Orders of Magnitude. Journal of Glaciology, 68(270), 651–664.