Weather Prediction: Forecast Snow Depth in Stockholm

Group 4 - Natalia Rodriguez, Pierre Grégoire Malo Jousselin, Xi Sun

Abstract

This study explores ML models to predict snow depth and temperature based on historical weather data from Stockholm. The primary goal was to develop accurate, short-term forecasts for snow depth and temperature to aid in winter human activities and operations. We trained models on weather data from 2021 and 2022 to predict conditions for 2023. While deep learning models like LSTM were expected to perform well, the Random Forest regression model ultimately delivered the best results, offering both accuracy and interpretability.

1. Introduction

1.1. Background

Weather prediction is an important area in climate science, as it impacts ecosystems, water resources, and human activities. One particularly important aspect of this is predicting snow depth, especially for regions that rely on winter tourism or where snow removal is essential for daily activities like Stockholm. Understanding snow depth patterns is also essential for planning infrastructure, and forecasting water supply from snowmelt (Sukanya et a., 2023). With climate change, traditional patterns of snowfall are becoming more unpredictable, making accurate snow depth forecasting increasingly important (Hock et al., 2021).

Predicting snow depth, however, is not straightforward. Snow accumulation is influenced by a variety of factors, including temperature, precipitation, wind, and air pressure(DeWalle et al., 2008). Each of these elements interacts in complex ways, making snow depth forecasting a multi-dimensional problem (Pomeroy et al., 2002). Traditional models like physical models have their limitations, especially when facing extreme weather conditions, often failing to capture long-term trends and variability caused by global climate change.

1.2. Related Research

Researchers have applied ML to various climate-related problems, such as temperature prediction, precipitation forecasting (Tripathy et al., 2023), and snow depth estimation (Girotto et al., 2020). For instance, Girotto et al. (2020) used remote sensing data and ML models to estimate snow depth over large geographic areas. Their study demonstrated that machine learning models, particularly those leveraging historical data, can outperform traditional methods in predicting snow-related variables. Similarly, researchers like Meyal et al., (2020) have applied deep learning techniques, such as Long Short-Term Memory (LSTM) networks, to time series data, showing success in capturing the non-linear patterns in snow depth and snowfall.

Based on the existing ML models that have been proved to have the potential of predicting weather changes. This project is to analyze historical weather data in Stockholm to predict its future climate trends and changes.

In this study, we aim to narrow this gap by focusing on weather patterns, such as temperature fluctuations and snow depth are affected over time.

2. Research Question and Method Description

Our research focuses on using historical weather data to predict snow depth accurately, and providing insights for winter activities such as skiing and snow removal. We leverage a range of machine learning models—including Neural Networks, Non-Linear Regression, LSTM, and Random Forest—each chosen for its unique ability to handle different facets of the data, from temporal dependencies to non-linear interactions.

2.1. Story

In 2021 and 2022, Stockholm experienced unpredictable changes in snow depth and temperature. For example, certain periods saw unexpected spikes in temperature or snowfall that didn't match the seasonal averages. We gathered detailed weather data from these two years to understand the trends better and see if they can help us forecast future weather conditions.

We're using this historical data to predict the snow depth and temperature for 2023. Different machine learning models are being used to see how accurately we can forecast 2023's weather based on past data. We are exploring a neural network for complex pattern recognition, LSTM for capturing time-based dependencies, and other models like Random Forest and Non-Linear Regression to evaluate which model gives the most precise prediction.

The variability in weather patterns during 2021 and 2022 could be influenced by multiple factors, including regional climate conditions and broader global climate shifts. Our models will help determine which factors (such as previous snowfall, temperature changes, or seasonality) are most impactful in predicting future snow depth and temperature. We're testing different models to identify which provides the best explanation and prediction accuracy.

By applying these models, we aim to predict what will happen in 2023 regarding snow depth and temperature. Based on initial results, some models, like LSTM and Neural Networks, show promise in capturing seasonal trends and forecasting sudden shifts, while others like Random Forest may struggle with the complexity of the data. This will help us conclude which model can best anticipate changes in snow and temperature.

Once we identify the best-performing model, it could serve as a tool for local authorities and businesses in Stockholm to prepare better for snow events or extreme temperatures in 2023. Accurate forecasting would allow for better winter road maintenance planning, public safety measures, and even energy use predictions for heating.

2.2. Research Question

How accurately can snow depth and temperature in Stockholm for 2023 be predicted using supervised machine learning models trained on weather data from 2021 and 2022, and which model provides the most reliable forecast?

2.3. Hypothesis

Prediction combined with historical weather data, especially temperature, can be more accurate and effective. Specifically, models that capture temporal dependencies (LSTMs) and Neural Network model will outperform simpler models in forecasting snow depth and temperature.

2.4. Programming Framework

For the implementation of the predictive models, we will be using Python as the primary programming language due to its versatility and wide range of libraries suitable for data analysis and machine learning. Specifically, we will use the Scikit-learn library for traditional learning models such as Random Forest, and Nonlinear Regression. For deep learning approaches like Neural Networks and Lon Short-Term Memory (LSTM) models, we will use TensorFlow, which provides robust tools for building and training complex neural networks. To visualize and analyze model performance, we will rely on Matplotlib, a library for creating graphs and plots. These frameworks will allow us to efficiently process the weather data and test the predictive accuracy of different models.

2.5. Data

The data used in this project consists of weather record from Stockholm, covering years 2021 and 2022, including variables such as snow depth, temperature (average, minimum, and max), station ID, city, date, season, average wind (direction, speed), sunshine, sea level pressure, and other relevant meteorological indicators. The data was collected from weather stations ensuring accuracy and reliability. Prior to training the models, we preprocessed the data including handling missing values and normalizing variables. The cleaned data was divided into training and testing sets, where data from 2021 and 2022 was used to train the machine learning models, and the data from 2023 was used for testing.

2.6. Classifiers

These were the classifiers used to predict snow depth and temperature for 2023:

- Neural Networks: were chosen for their ability to model complex, non-linear relationships in the data. A neural network can capture hidden interactions between features like temperature and snow depth (Yang et al., 2022).
- Non-Linear Regression: selected to model potentially non-linear relationships between weather variables (Bochenek & Ustrnul, 2022).
- Long Short-Term Memory (LSTM): this was chosen because it is ideal for time-series data like weather patterns. By maintaining memory of previous data points, LSTM can capture temporal dependencies (Li & Qian, 2024).
- Random Forest Regression: was included for its capacity in handling noisy data and its ability to merge a mix of numerical and categorical variables (Hill et al., 2020).

3. Research Process

For this project we designed a structured research to predict snow depth and temperature for Stockholm in 2023 using historical data from 2021 and 2022. This involved several stages, from defining the research question and planning the story to data collection, model, implementation, and evaluation. Here is how we approached each step:

3.1. Type of Story

We planned to tell a data-driven, predictive story that illustrates how historical weather patterns can be used to forecast future conditions. We concentrated on temperature and snow depth since they are two important factors for the general public and industries affected by weather. Our story aimed to reveal how accurately machine learning models can predict these variables for 2023, showing insights from past weather trends in Stockholm.

3.2. Story Appreciation

We ensured that the story would be appreciated by focusing on a real world problem that has practical implications. Snow depth and temperature predictions are significant for urban planning, transportation management, and public safety in Stockholm. We make our narrative relevant to both technical and non-technical audiences by determining it in measurable outcomes.

3.3. Connecting Story with Research Question

We connected the story to the research question by focusing on how the data and models help understand and predict future weather conditions. The goal was to predict snow depth and temperature for 2023 based on data from 2021 and 2022, so the story revolves around that process. First, we looked into the historical data to understand weather trends. Then, we used machine learning models to forecast what the weather might look like in 2023. Finally, we compared the models to see which provided the most accurate predictions. The logic flow of the story showed how each part of the project helped us answer the research question.

3.4. Open-Ended Subquestions

To delve deeper into the research, we formulated these open-ended subquestions:

- Which features have the most significant impact on predicting snow depth and temperature?
- How do the predictions change when using different machine learning models?
- What challenges arise in predicting extreme weather events, and how can models be adjusted to improve these predictions?

3.5. Challenges in Data Collection

These were the challenges we faced during the data collection:

- Missing Data: Some weather stations had incomplete data for the key features, snow depth and temperature.
- Data Quality: There were some unusual high or low temperatures and needed to be handled to avoid affecting the model training process.
- We Need More Data: Because the prediction focuses only on Stockholm, if we want to use a complex model to predict, we need to have a certain amount of data to fit the model better.

These were the data fixes we implemented:

- Mean imputation for continuous variables (like temperature and snow depth) by calculating the average from nearby days.

- For unusual temperatures we try to smooth these outliers.
- More weather stations. And we extended the time period.

4. Results

As we can see we tried fitting an Exponential Model to visualize the trend of the yearly temperature in stockholm. This graph shows the model prediction and the prediction interval. Even though the points are a bit spaced to model prediction most of the points fit inside the prediction interval with approximately the same number of points either above or below the model curve. Therefore the model still fits well. The conclusion is that the average temperature seems to be increasing faster and faster.

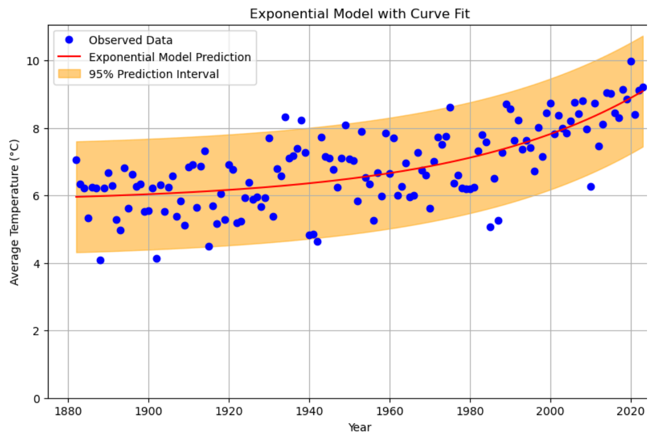

Figure 1

4.1. Snow Predictions

First of all we wanted to see if we could observe a trend in the yearly snow depth, but the result was that it seems very random with the snow depth varying a lot between the years and seems not to decrease that much in the recent years.

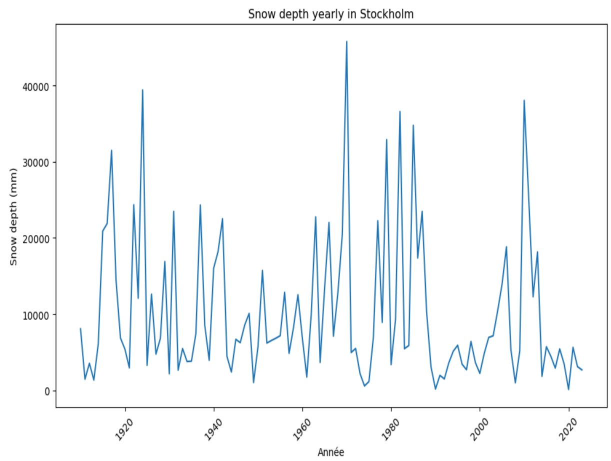

Figure 2

Neural Networks

One of the approaches is to train a Neural network using the data from the past days as input. The architecture of the network consists of 5 fully connected layers using the ReLu activation function. In order to prevent overfitting we plotted the loss function of the training set and in the validation set

Figure 3

We then plotted the result of the predicted values for the unseen data vs real value.

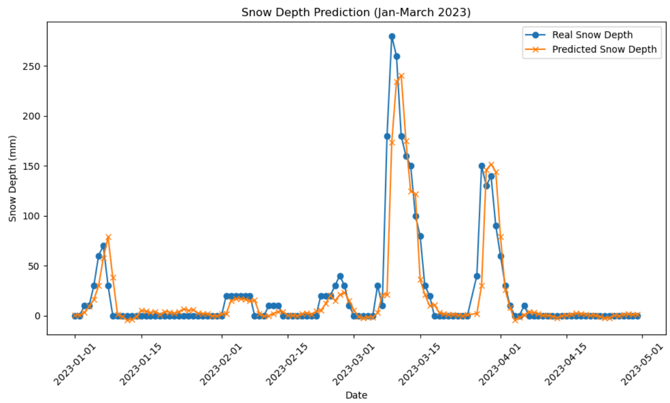

Figure 4

As we can see the model has found a way to approximate the snow depth of the next day. We can see that the peaks are a bit sifted on the right. Which can be explained because the model tends to follow the slope of the past day and therefore as a bit of delay. This problem is generally an important problem with time series prediction on time series that heavily depends on what happened just before.

LSTM

Another model used the architecture of LSTM which stands for (long short term memory). LSTM are known for the capacity to process time series using memory cells and have a more efficient backpropagation in time.

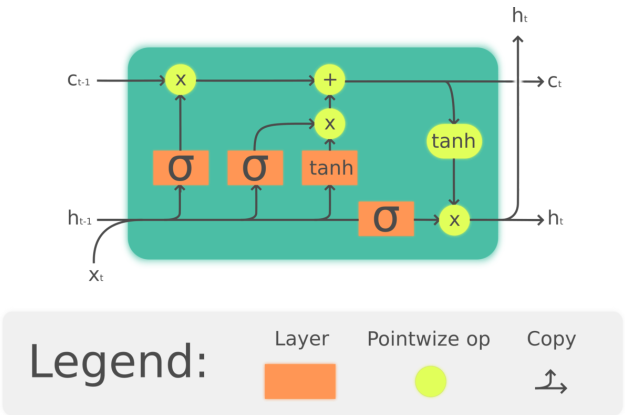

Figure 5

Each unit has 3 inputs and 2 outputs. The three inputs are, the data input x(t), the output of the previous nodes h(t-1) and the previous memory cell output c(t-1). The two outputs are the node output h(t) and the memory cell output c(t).

As we did with neural networks we used the data of the past days as input for our LSTM model. The result is shown below

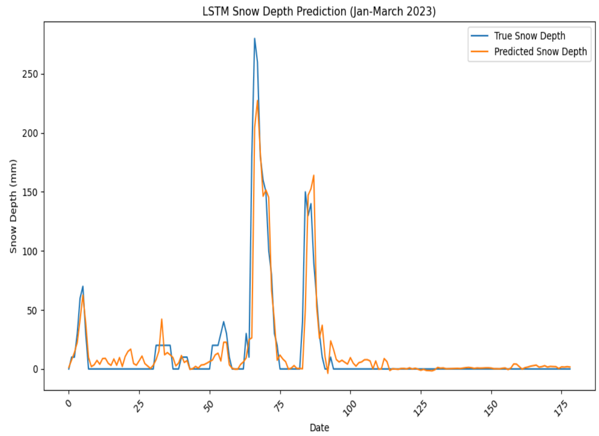

Figure 6

Random Forest Regression

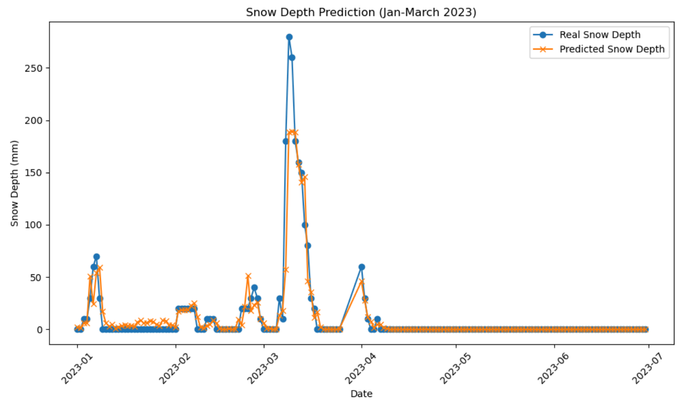

Figure 7

Result:

	Neural Network	*LSTM*	*Random Forest*
MSE	*292.95*	*162.01*	*110.8*
MAE	*9.97*	*7.46*	*5.04*

4.2. Temperature Predictions

As we trained our network to predict snow depth using the data from the previous year we wondered if we could predict other parameters like the temperature in order to help our snow predictions model.

Neural Network

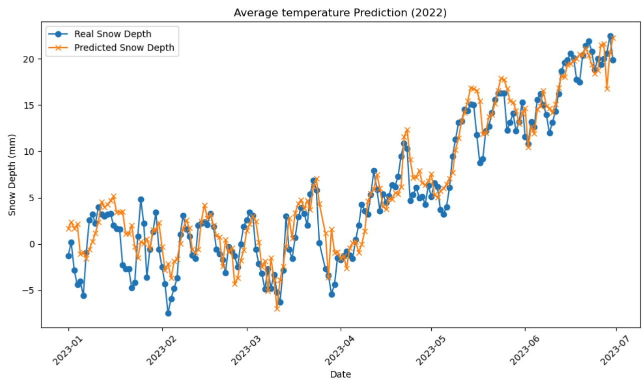

Figure 8

In order to have a better visualization of our prediction and see if there is any bias we plotted the graph comparing our predicted temperature in function of the real temperature. Ideally if the model is perfect it produces a line.

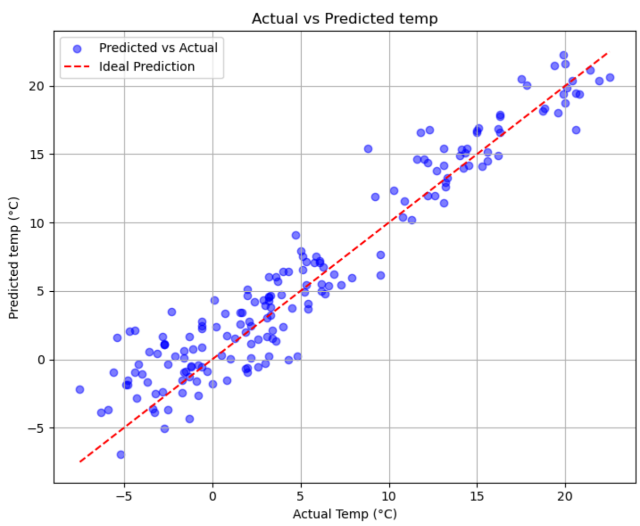

Figure 9

As we can see the model follows the lines but still has a large variance. At least we can observe that the number of points above and below the line is very close which means that the model seems to have no bias .

The regression score using this model is: R2_score=0.91

LSTM

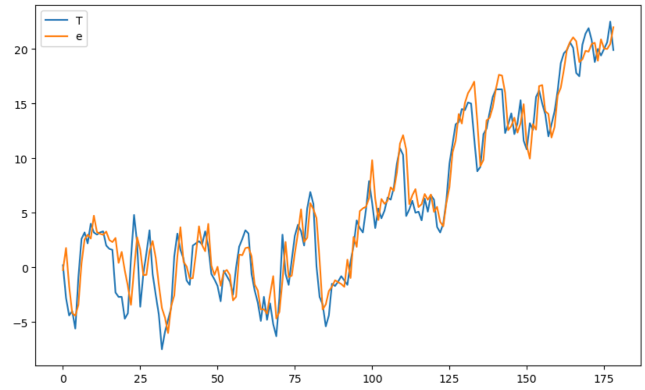

Figure 10

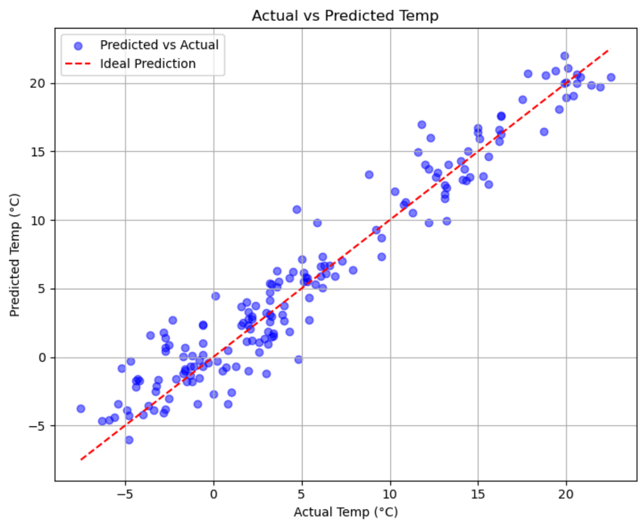

Figure 11

Random Forest Regression

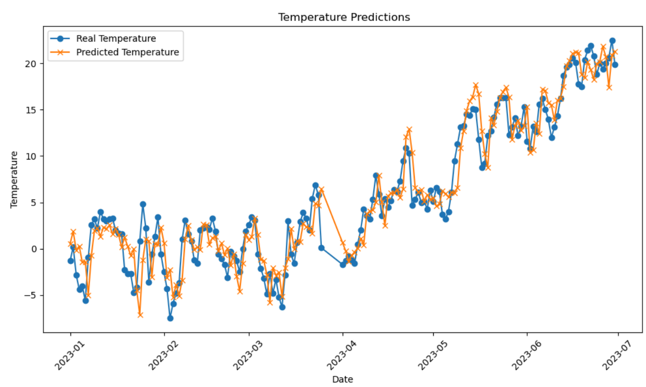

Figure 12

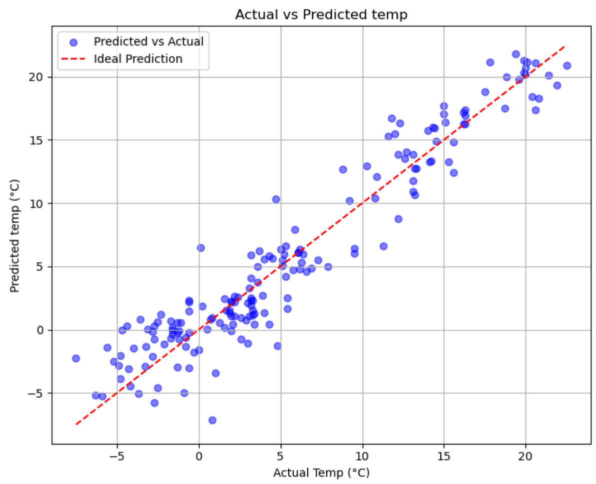

Figure 13

	Neural Network	*LSTM*	*Random Forest*
MSE	*2.76*	*2*	*0.07*
MAE	*1.87*	*1.55*	*0.17*
R^2	*0.91*	*0.934*	*0.91*

5. Discussion and Reflection

This study aimed to predict snow depth and temperature using historical weather data. The core research question was: How can historical weather data be utilized to predict snow depth and temperature, and what insights can be drawn to optimize winter operations, such as skiing and snow removal? The result turns out that Random Forest performs best, LSTM outperforms the Neural Network.

For the data collection and the processing. Since our prediction focused solely on Stockholm, the dataset was somewhat limited. Complex models like LSTM and especially the Neural Network require a large amount of data to perform well. We extended the time period. Some data is missing key metrics and there were also instances of strange temperature spikes, which we suspected were errors. To solve this, we applied techniques to fill in the missing data and smooth out the outliers.

Choosing the right models was another key challenge. LSTM, which is great at handling time-series data, captured how previous weather conditions influence current snow depth. Neural Networks helped us uncover hidden relationships between different weather variables, but because we chose to focus on weather data in Stockholm, making the Neural Network model underfit, it didn't perform as well as we thought. Random Forest gave us insights into features that were more important, and this simple model performed the best.

Through this project, we use lagged features to capture how past weather affects future snow depth and temperature. We explored a range of models to compare their abilities towards this problem, because of some underfitting problems, the complex model didn't outperform the simple Random Forest. But the Random Forest Regression provided a very good result of prediction. These predictions can be translated into practical insights, helping municipalities plan snow removal and skiers plan their trips.

There is a potential bias introduced by the reliance on historical data, especially if climate change or extreme weather events have altered snow patterns significantly. This could lead to underestimating future changes in snow depth or temperature.

For future direction, expanding the dataset to include more cities or regions with diverse weather patterns would make the model more generalizable. Using this prediction, people could predict peak skiing times during the winter season by forecasting when snow depth will reach an optimal level. A real-time snow prediction tool could turn these models into practical solutions for day-to-day operations.

6. Conclusion

Using historical data and city specific city weather conditions we were able to use machine learning models to predict both snow depth and temperature of the next day.The results obtained allow the user to have a good estimate of the next day's weather forecast on snow depth and temperature. It could allow the city to prepare accordingly in the event of high snow depth to prepare the roads and if the temperature drops to be aware that there will be an increase in energy consumption due to the heating systems.

In conclusion, this project aimed to predict snow depth and temperature for Stockholm in 2023 using machine learning models trained on weather data from 2021 and 2022. Even though we could expect the LSTM model to outperform other models, it wasn't the case with those data. Our results demonstrate that the Random Forest regression model outperformed the other models in predicting both snow depth and temperature. It also has the advantages of being more interpretable. Even if the other models have a higher capacity, the nature of the data makes it harder for neural network based models to learn efficiently and generalize well.

7. References

Sukanya, S., & Joseph, S. (2023). Climate change impacts on water resources: An overview. Visualization Techniques for Climate Change with Machine Learning and Artificial Intelligence, 55-76.

Hock, Regine, and Matthias Huss. "Glaciers and climate change." Climate change. Elsevier, 2021. 157-176.

DeWalle, D. R., & Rango, A. (2008). Principles of snow hydrology. Cambridge University Press.

Pomeroy, J. W., Gray, D. M., Hedstrom, N. R., & Janowicz, J. R. (2002). Prediction of seasonal snow accumulation in cold climate forests. Hydrological Processes, 16(18), 3543-3558.

Tripathy, K. P., & Mishra, A. K. (2023). Deep learning in hydrology and water resources disciplines: Concepts, methods, applications, and research directions. Journal of Hydrology, 130458.

Girotto, M., Musselman, K. N., & Essery, R. L. (2020). Data assimilation improves estimates of climate-sensitive seasonal snow. Current Climate Change Reports, 6, 81-94.

Bochenek, B., & Ustrnul, Z. (2022). Machine learning in weather prediction and climate analyses—Applications and perspectives. Atmosphere, 13(2), Article 2.

Hill, A. J., Herman, G. R., & Schumacher, R. S. (2020). Forecasting severe weather with random forests.

Li, B., & Qian, Y. (2024). Weather prediction using CNN-LSTM for time series analysis: A case study on Delhi temperature data. arXiv. https://arxiv.org/abs/2409.09414.

Meyal, A. Y., Versteeg, R., Alper, E., Johnson, D., Rodzianko, A., Franklin, M., & Wainwright, H. (2020). Automated cloud based long short-term memory neural network based SWE prediction. Frontiers in Water, 2, 574917.

Yang, J., Jiang, L., Pan, J., Shi, J., Wu, S., Wang, J., & Pan, F. (2022). Comparison of machine learning-based snow depth estimates and development of a new operational retrieval algorithm over China. Remote Sensing, 14(12), Article 12.

8. Appendix

8.1. Project Assessment

Natalia's Project Assessment
Reflecting on my learning experience, I delved deeper into analyzing data and predicting weather patterns, gaining experience with time series models and data visualization tools. I found it both interesting and challenging to use ChatGPT for this project, as we are usually not permitted to use it much. However, I discovered that it was a great tool for working with data analysis, machine learning, and even for helping ideate a storytelling approach to present the data. Initially, I found it challenging because it had been about three years since I last studied machine learning, so I had to refresh my memory. Fortunately, I was able to grasp the concepts quickly.

I committed to this project by setting clear goals from the beginning. I attended all group meetings and completed all the tasks we divided during each session. I also attended all lectures to learn about the relevant topics and conducted additional research by watching videos and reading articles on weather predictions and machine learning.

The team had excellent communication. We held weekly group meetings where we defined the goals for the week. I believe we divided the work evenly, and each team member completed their tasks on time and responsibly.

Pierre's Project Assessment
From a personal point of view I found the project interesting and it presented some challenges. I had never worked before with weather data. We managed to have running models and promising results. We managed to have different metric scores and good visualization graphs.

I committed to the project in order to have a deeper understanding of more complex models like LSTM. It also took a lot of time to help others with codes and bring the result together with the same metric in order to be able to compare the model together.

The team functioned well. Even though I was the only one with a machine learning background the team was motivated and learned very quickly the different challenges that we needed to face. I am very happy with the development of the team. They bringed and helped me a lot especially in the visualization and how to show the different results.

To conclude, I was very happy with my team and the project even though there is still a lot of stuff to pursue in the project, I'm satisfied with the result obtained.

Xi's Project Assessment
The positive side of using lagged features to capture past weather's impact on future snow depth and temperature proved effective. Our data preprocessing, particularly handling missing data and outliers, helped improve model performance. However, the limited dataset from Stockholm posed difficulties for complex models like LSTM and Neural Networks, leading to under-fitting results. Surprisingly, the simpler Random Forest model outperformed others, highlighting the importance of choosing the right model for the data at hand.

One key area of my growth is in understanding how different machine learning models behave with time-series data and how to process the data, dealing with data gaps or outliers that arise in real-world datasets. Also I learned that while using complex models, even though they are said to be better at solving complicated problems, they also need complex and enough context to perform better.

Our team functioned well overall, with open communication and clear task division. We collaborated effectively on data preparation, model selection, and analysis. We committed to analyzing different models that might suit this specific task according to their special characteristics.

8.2. Link to The Data Sets

https://drive.google.com/drive/folders/1n3rpK9sioc_7eM25Cv4xzZ9vkoV-rwbS?usp=drive_link

8.3. Link to Python Code

https://drive.google.com/drive/folders/10OJ7BtDx09rh6PnFNyk5ssAVr9iGjwzW?usp=drive_link