Imperial College London
Department of Earth Science and Engineering
MSc in Environmental Data Science and Machine Learning

Independent Research Project
Project Plan

Monitoring Mountain Water Resources through Space and Time with Deep Learning

by

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Abstract

The study aims to enhance daily Snow Water Equivalent (SWE) estimates, critical for managing water resources, mitigating flooding, and understanding climate change impacts. Traditional snow depth to SWE conversion methods, such as thermodynamic snow model, and empirical regression models (ERMs), show limitations, particularly for lowering data requirements and enhancing temporal resolutions. As a solution, a novel architecture integrating Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM) is proposed, exploiting the advantages of deep learning to capture spatial-temporal snowpack dynamics. The model will use the snow depth as input to estimate SWE maps. The project also implements ensemble training to enhance model's transferability. Additionally, the snow classification scheme will be employed to further improve the model's transferability. Advanced feature selection is planned to mitigate data constraints and overfitting issues, thus potentially improving the model's performance.

Introduction

1 Literature review

Snow Water Equivalent (SWE) is essential for managing water resources, producing hydropower, preventing floods, and more, especially in places like California where the annual April snowpack water storage is almost twice as large as surface water reservoir storage (Siirila-Woodburn et al., 2021). Accurate estimation of SWE is crucial for a few reasons. It can first help with forecasting snowmelt water. Snowmelt water is used for agriculture and human consumption by about one sixth of the world's population (1.2 billion people) (Barnett et al., 2005). Furthermore, if the accurate peak SWE value can be provided, it can also aid in early-warning for the flooding.

Traditionally, SWE is estimated by converting snow depth measurements using snow density estimates. There methods, including Thermodynamic Snow Models, Empirical Regression Models (ERMs) and Semiempirical Models, each has its strengths and limitations. For example, modern thermodynamic snow models focus on mass and energy balance within the ground-snow-atmosphere system but often have high requirements on specific atmosphere variables (Winkler et al., 2021). ERMs, such as the models proposed by (McCreight and Small, 2014), and by (Jonas et al., 2009), strongly relies on the linear relationship between snow depth and SWE. However, these models may not be able to convert time series of snow depth into SWE at a daily resolution or higher (Jonas et al., 2009), which make it unsuitable for certain applications such as water resources management which requires high-resolution data. In addition, some of ERMs also have a high data requirements, for instance, the models by (McCreight and Small, 2014), require at least three training dataset of snow depth and SWE from nearby stations for their model. The semiempirical models combine theoretical principles and empirical observations. These models do not require any additional meteorological inputs (snow depth is the only required input) and can simulate individual snow layers (Winkler et al., 2021), which make them easily-used and more suitable for analysing the snow accumulation process. But they still have some limitations, for instance, these models significantly depend on the initial condition such as density (Winkler et al., 2021). Some of these models are more suitable in specific area, for example, the models by (Sturm et al., 2010) suits for use in sparsely populated places like the Arctic.

There has been some promising development on the estimating SWE by using deep learning models, such as Artificial Neural Networks (ANNs) by (Ntokas et al., 2021). However, the model still has relatively high data requirements, including ‘days without snow since the beginning of winter', 'total solid precipitation in the last 10 days', and more, which limits its applications.

2 Problem Description

Given the existing models including Thermodynamic Snow Models, ERMs and Semiempirical Models, each of them has its limitations. These limitations include high data requirements, lack of transferability and inability to provide daily change. Therefore, there is a need to develop a new model to address these limitations.

The dataset of this project will use 50 metres resolution snow depth and SWE maps measured by the Airborne Snow Observatory (ASO), which covers several basins (Figure 1) from 3 April 2013 to 16 July 2019 ("ASO L4 Lidar Snow Water Equivalent 50m UTM Grid, Version 1," 2020). The snow depth maps will be used as the input data and the SWE maps will be used as the target value.

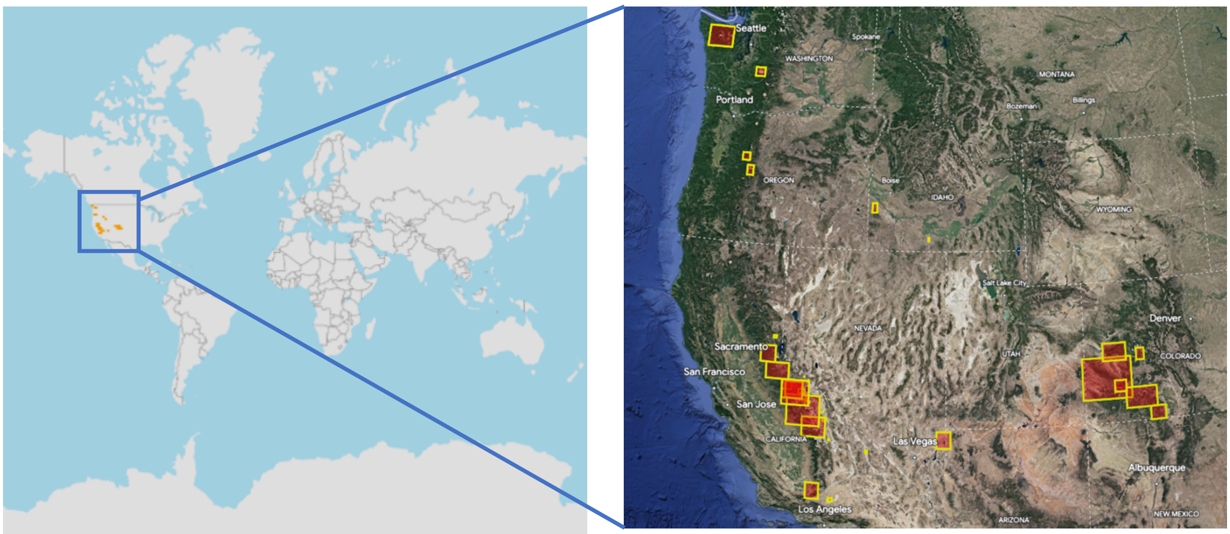

Figure 1. (a) Yellow areas on the map above indicate the spatial coverage for this dataset. Image from ("ASO L4 Lidar Snow Water Equivalent 50m UTM Grid, Version 1," 2020). (b) The detailed locations of covered area for the dataset.

3 Objective

This project aims to propose a novel architecture combining Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM), known as ConvLSTM. The choice of ConvLSTM is mainly because it combines the strengths of CNNs and LSTMs. CNNs are well-suited for processing image data (Albawi et al., 2017), making them ideal for analysing the spatial complexity of SWE maps. In the real world, snowpack conditions are usually affected by the neighbouring regions due to the spatial correlation, for example, the wind direction can cause snow moving and re-distributing. Hence an algorithm that can capture these spatial relationships would likely perform better than one that models each pixel independently. In addition, LSTMs have unique abilities to process time-series data by remembering patterns over time, which can capture the temporal evolution of snowpack dynamics. Some experiments have proved that ConvLSTM performs better than a single LSTM on multivariate noise time series data (Jin et al., 2020). Therefore, ConvLSTM is expected to capture more detailed spatial-temporal information, producing more accurate and reliable daily SWE maps.

The primary focus of this project will be on developing a ConvLSTM model that achieves a high spatial resolution and accuracy. After that, future work in this research, as shown on Figure 2, will focus on reducing data requirements and expanding the areas of transferability

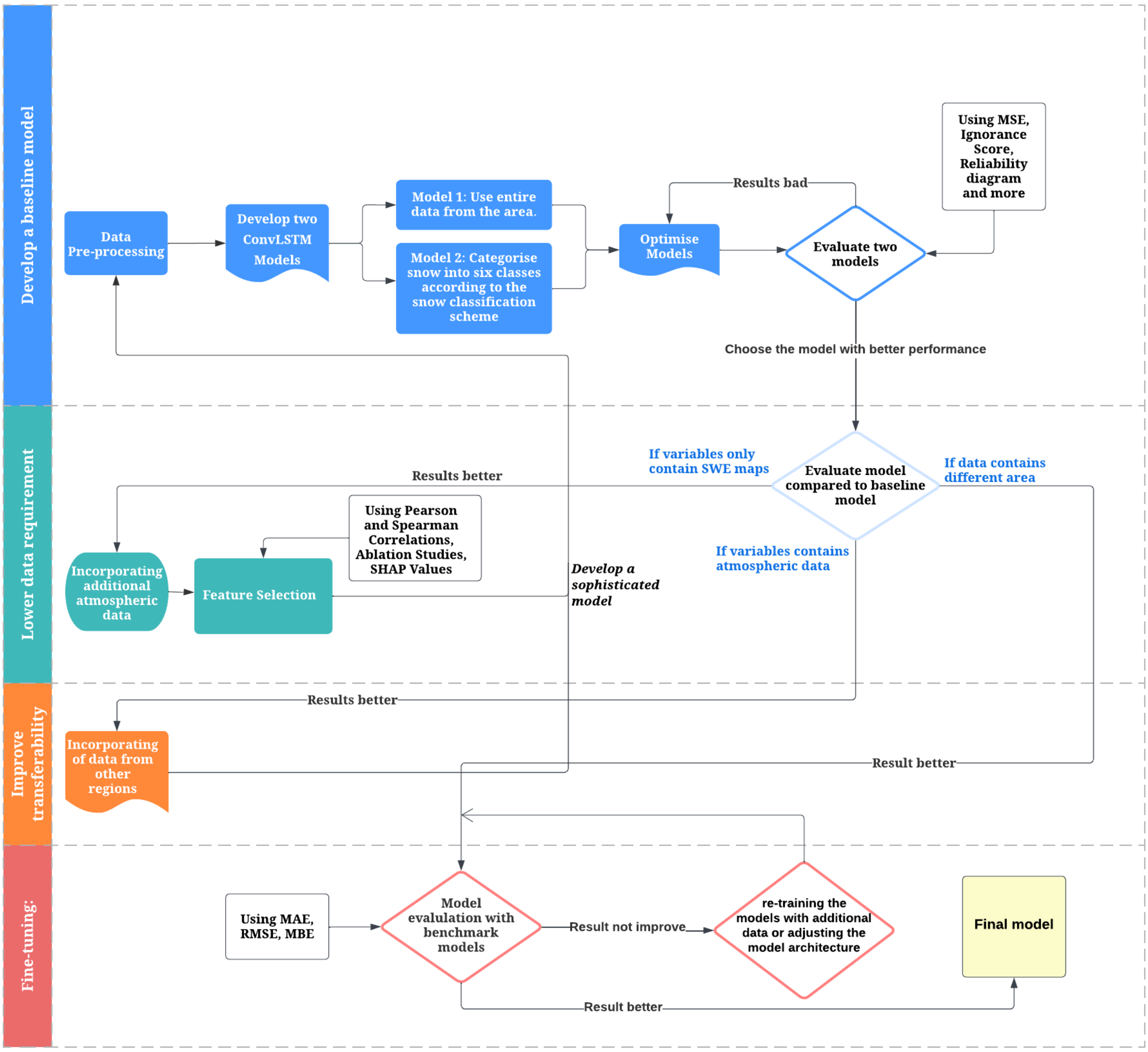

Figure 2. The future workflow of the project

ensuring the model's ability to be applied across a range of geographic area.

Progress to Date

After conducting literature reviews, I have outlined a comprehensive plan to improve SWE estimation. In addition, I have also performed data analysis on open-source datasets.

Future Plan

The initial focus will be on data from the United States of America (USA), primarily using the SWE maps from Airborne Snow Observatory (ASO). This data will be pre-processed and well-organised for training. For instance, perturbations will be applied to SWE maps to reflect uncertainty in accordance with WMO's guideline, the error of snow depth measurements should not exceed ±1 cm if the snow depth is less than 20 cm and ±5 % if the snow depth is greater or equal to 20 cm (Organization, 2017). Moreover, the snow classification scheme introduced by (Sturm et al., 1995) will be employed in ensemble training to improve model performance. We will then develop two different ConvLSTM models for the training data. The first model will use the entire data from the area, and the second will categorise snow into six classes for ensemble training according to the snow classification scheme (Sturm et al., 1995). This approach aims to provide more robust and accurate predictions. Different hyper-parameters and network architectures will be experimented with to optimise model's performance.

Furthermore, a more sophisticated model will be developed, incorporating atmospheric data, such as precipitation, temperature, humidity, and wind speed, from European Centre for Medium-Range Weather Forecasts (ECMWF), Global Precipitation Measurement (GPM), and SWE station data. Feature selection will be conducted by comparing the Pearson Correlation and Spearman Correlation to test the linear or non-linear relationship between the explanatory variables and SWE. In addition, I will also do the ablation studies, and use SHapley Additive exPlanations (SHAP) to see the features' importance.

After validating models on USA's data, I will extend the model to other regions by incorporating more data to enhance transferability. Depending on regional characteristics, I might add more climatic, geographic conditions, or physical properties of snow in the specific place to train more models.

Regarding the model performance evaluation, MAE, RMSE, and MBE will be used as the error metrics to evaluate the performance of the ConvLSTM model, as used by (Ntokas et al., 2021). Model performance will be compared with benchmark model - the MLP model by (Ntokas et al., 2021) and iSonbal (Marks et al., 1999), as shown in Table 1. Based on the results from these comparisons and validation, the models will be fine-tuned. This step may involve re-training the models with additional data or adjusting the model architecture to enhance performance.

	Single MLP ensemble model (SMLP)	Multiple MLP ensemble model (MMLP)	iSnobal in Mill-D station
MAE	32.8	29.3	/
RMSE	61.0	51.5	8.0
MBE	0.4	0.6	-5.0

Table 1. Performance evaluation metrics of the two MLP models (Ntokas et al., 2021) and iSnobal model in Mill-d station (Marks et al., 1999).

Overall, the expected outcome of the project is listed below:

- High-Accuracy Model: If everything goes well, the primary outcome would be the development of a highly accurate deep learning model for predicting SWE, which should have a relatively better result compared to the benchmark models.
- High Spatial Resolution: The model is expected to achieve high spatial resolution, specifically a resolution comparable to the ASO data (50 m resolution).
- Low Data Requirements: The developed model would require fewer data to make accurate predictions, making it a more feasible solution for areas where data collection is hard.
- Enhanced Transferability: Another expected outcome would be the model's ability to transfer to different regions. The aim is that the model could accurately predict SWE in various regions such as Switzerland, Canada, and the USA.

The timeline outlining the steps to achieve these outcomes is shown on Figure 3.

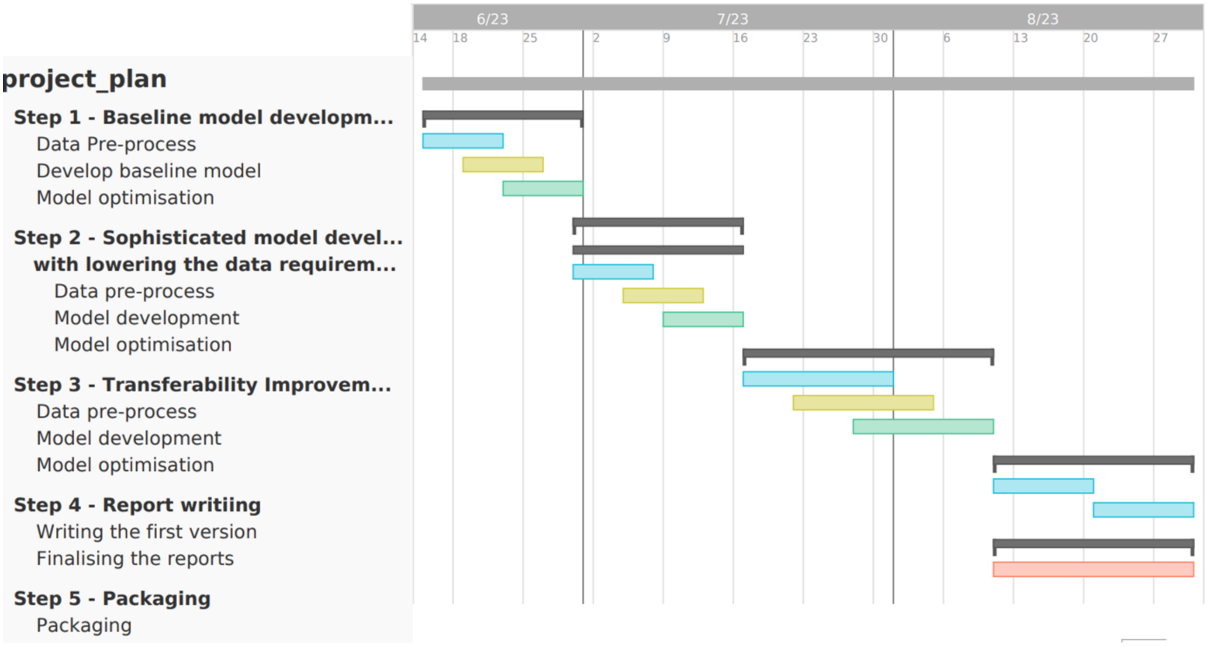

Figure 3. Estimated timeline for the project

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