ACCURATE ESTIMATION OF SNOW WATER EQUIVALENT (SWE) USING LONG SHORT-TERM MEMORY (LSTM)

Independent Research Project

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Background Introduction

Proposed Solution

Results

BACKGROUND INTRODUCTION

- THE IMPORTANCE OF SWE
- TRADITIONAL ESTIMATION METHODS
- DEEP LEARNING IN SWE ESTIMATION

BACKGROUND INTRODUCTION
THE IMPORTANCE OF SWE

- **Climate Change Impact**:
  - Consistent forecasts of near-surface warming due to greenhouse gases (Barnett et al., 2005).
  - Effects: Decreased winter snowfall, faster spring snow melt, shifted peak river runoff timing.
- **Significance of SWE**:
  - Defines the total water content in snowpack.
  - Essential for areas like California with major water storage in snowpack (Siirila-Woodburn et al., 2021).
  - Implications for agriculture, flood prevention, and daily water consumption for 1.2 billion people globally.

BACKGROUND INTRODUCTION
TRADITIONAL ESTIMATION METHODS

1. **Thermodynamic Snow Models**:
   1. Focus on mass and energy balances.
   2. High data requirements, especially atmospheric variables (Winkler et al., 2021).
2. **Empirical Regression Models (ERMs)**:
   1. Linear relationship between snow depth and SWE.
   2. Some of them are limited in daily resolution capacity (Jonas et al., 2009).
3. **Semi-empirical Models**:
   1. Combination of theory and empirical data.
   2. Dependence on initial conditions like density.

BACKGROUND INTRODUCTION
DEEP LEARNING IN SWE ESTIMATION

Artificial Neural Networks (ANNs):

1. Recent advancements in SWE estimation (Ntokas et al., 2021).
2. **Challenges**:
    1. Specific high data requirements, such as ‘days without snow since the beginning of winter’, and ‘total solid precipitation in the last 10 days’.
    2. Only focus on a specific region

PROPOSED SOLUTION

Data Overview

Methods Overview

1. Data Pre-processing
2. LSTM Model Construction

DATA OVERVIEW

Snow depth and SWE:

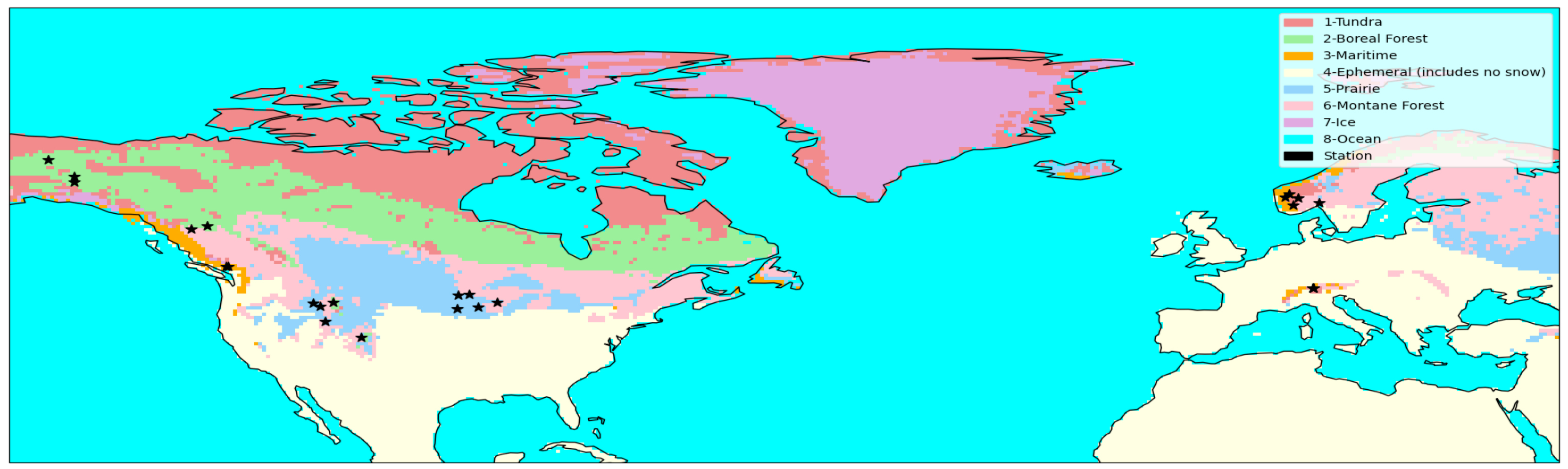
- Total Records: **35,811** daily entries.
- Covered Regions: Norway 🇳🇴, Canada 🇨🇦, Switzerland 🇨🇭, and United State of America 🇺🇸.

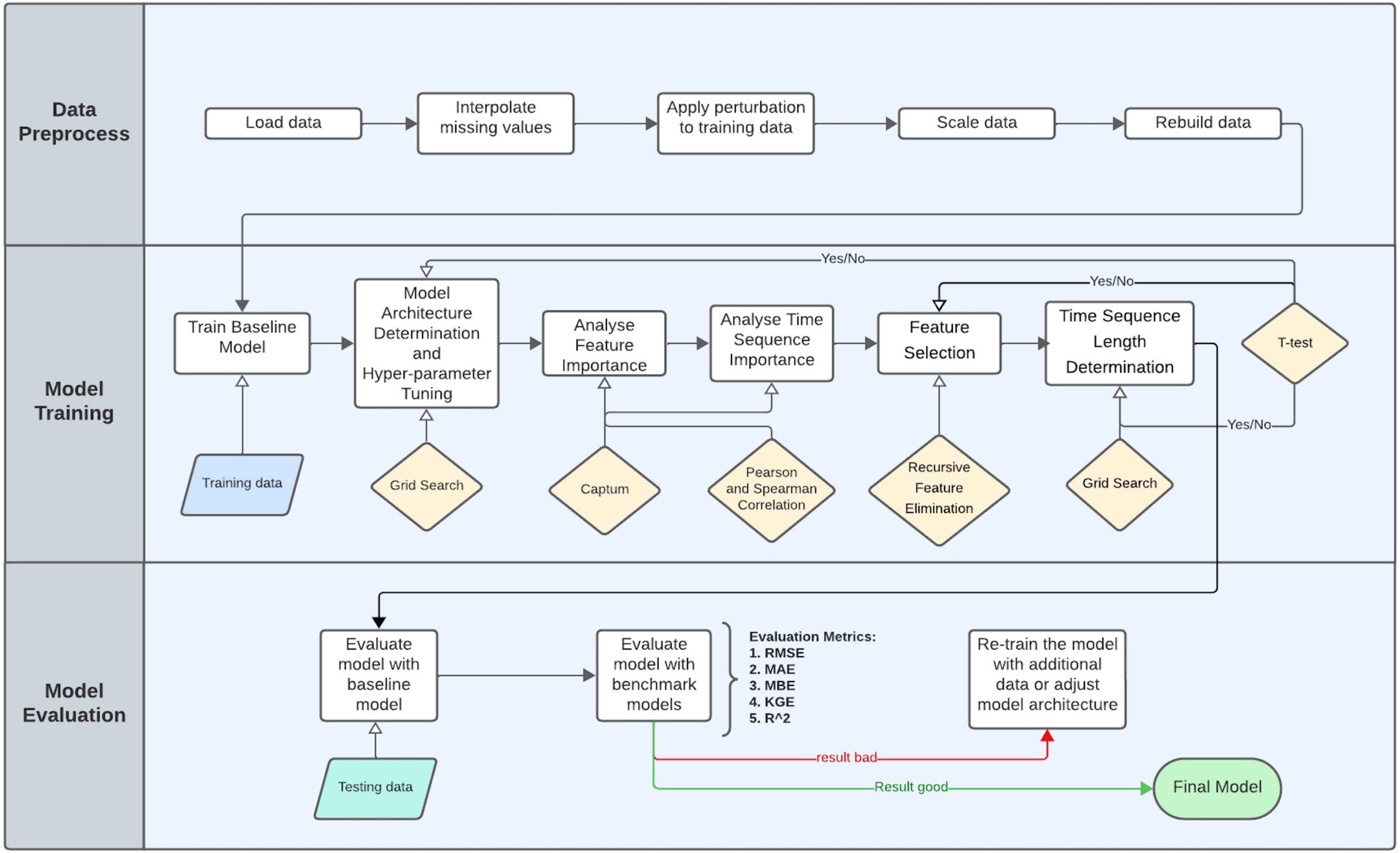
Meteorological Variables:

- Source: ERA5-Land hourly data (1950-present).
- Features Retrieved: **Temperature** (°C), **Precipitation** (m), **Snowfall** (m of water equivalent), **Solar radiation** (J m^{-2})

Snow Classification Scheme:

- Dataset: Global Seasonal-Snow Classification by [(Liston & Sturm, 2021)]
- Classes: **Tundra, Boreal Forest, Maritime, Prairie, Montane Forest**.




Data Preprocess
Load data
Interpolate missing values
Apply perturbation to training data
Scale data
Rebuild data
Model Training
Train Baseline Model
Model Architecture Determination and Hyper-parameter Tuning
Analyse Feature Importance
Analyse Time Sequence Importance
Feature Selection
Time Sequence Length Determination
T-test
Yes/No
Yes/No
Yes/No
Training data
Grid Search
Captum
Pearson and Spearman Correlation
Recursive Feature Elimination
Grid Search
Model Evaluation
Evaluate model with baseline model
Evaluate model with benchmark models
Evaluation Metrics:
1. RMSE
2. MAE
3. MBE
4. KGE
5. R^2
Re-train the model with additional data or adjust model architecture
Testing data
result bad
Result good
Final Model

METHOD OVERVIEW

DATA PRE-PROCESSING

1. Split data
2. Interpolating missing values.
3. Applying perturbations based on WMO’s guidelines.
4. Scaling.
5. Rebuilding the input data to the required shape

Single Long Short Term Memory Model

SLSTM: Utilise the entire dataset

Muti Long Short Term

Model Architectures: Evaluated using Grid Search (1-4 layers).
Number of Neurons: Tuned via Grid Search.

Feature Selection:
1. Utilisation of 'Captum' tool.
2. Pearson and Spearman Correlation.
3. Recursive Feature Elimination.

Key Metrics: RMSE, MAE, MBE, KGE, R^2.

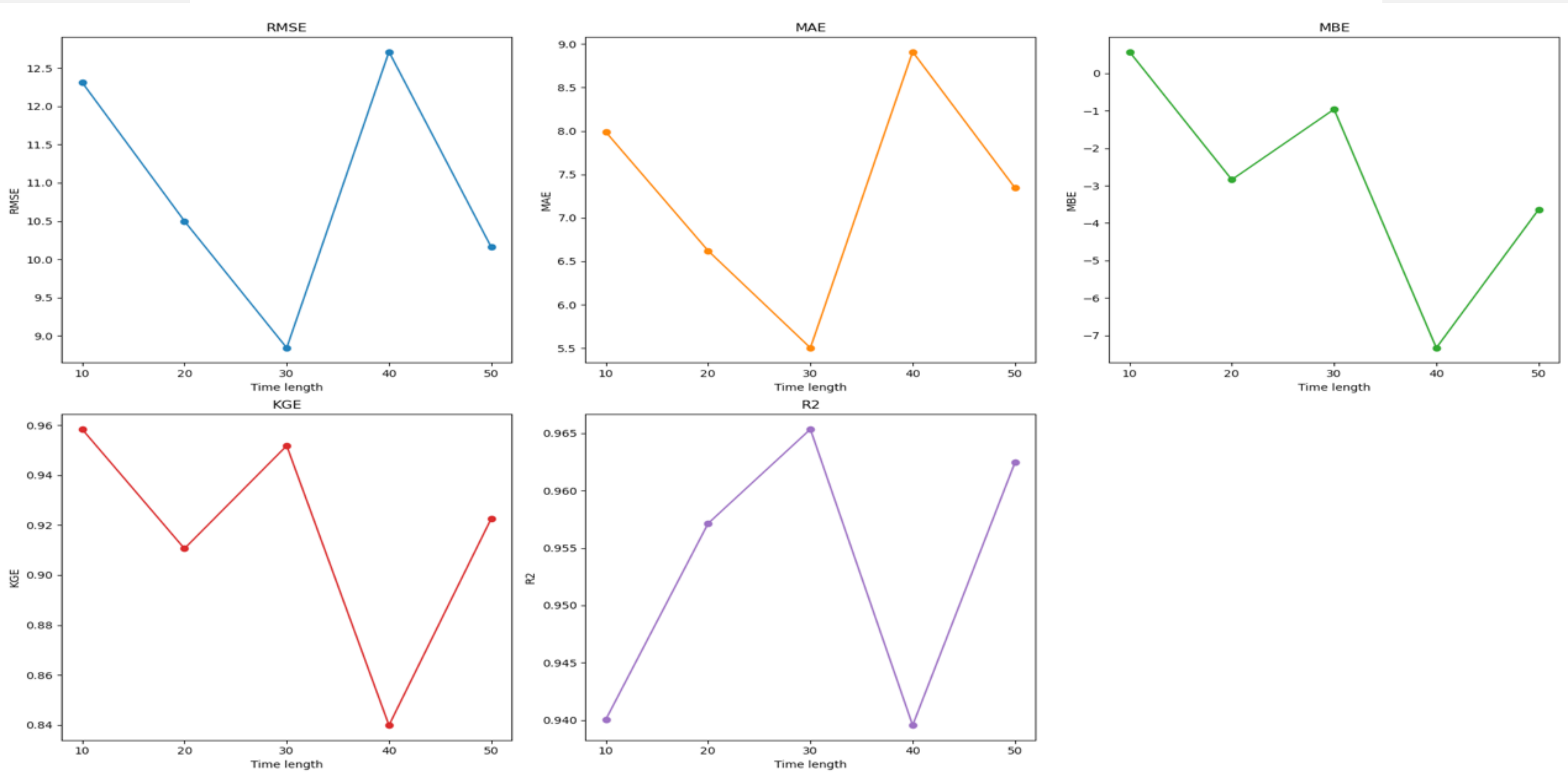
1. Model Construction

2. Hyper-parameter Tuning & Architecture Adjustment

3. Meteorological Variables & Time Sequence Selection

4. Model Evaluation Metrics

METHOD OVERVIEW
METEOROLOGICAL VARIABLES & TIME SEQUENCE SELECTION



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RESULTS

RESULTS
COMPARISON BETWEEN BENCHMARK MODELS

1. **Performance Differences**:
   1. Both SLSTM and MLSTM shows better MAE and RMSE values compared to the benchmark models such as iSnobal model and ANN models.
   2. The bias (MBE) for MLSTM is lower than both SMLP and MMLP.

	SLSTM	MLSTM	Single MLP ensemble model (SMLP)	Multiple MLP ensemble model (MMLP)	iSnobal in Mill-D station
MAE (cm)	3.816	3.679	32.8	29.3	/
RMSE (cm)	6.837	6.512	61.0	51.5	8.0
MBE (cm)	-2.060	-0.049	0.4	0.6	-5.0
KGE	0.895	0.969	/	/	/
R^2	0.969	0.970	/	/	/

RESULTS
COMPARISON BETWEEN MODELS

Performance Highlights:

1. MLSTM outperforms SLSTM across all metrics.
2. MAE and RMSE for MLSTM are reduced by 4.68% and 3.59% respectively compared to SLSTM.
3. MBE for MLSTM drops by 76.21% from -2.060 cm to -0.049 cm.
4. Both SLSTM and MLSTM have a strong R^2 close to 1.
5. MLSTM's superior KGE score indicates better alignment with observed values on the test set.

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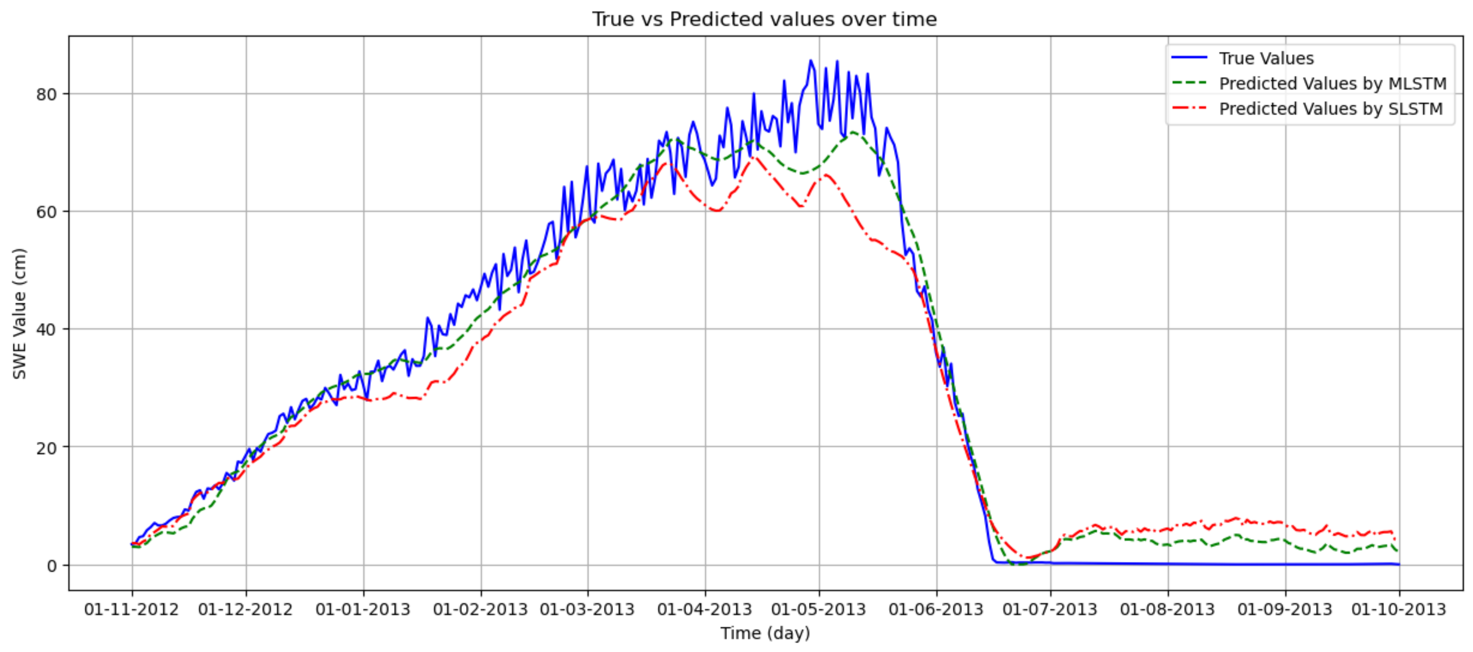

RESULT
COMPARISON BETWEEN MODELS

Performance Highlights:

- Based on data from one of Canada station, MLSTM's predictions align more closely with the actual values.
- MLSTM shows no obvious overfitting patterns, emphasizing its reliability and accuracy.

THANK YOU!