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Snow Water Equivalent Forecasting in Sub-Arctic and Arctic Regions with Recurrent Neural Networks

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Introduction

Snow water equivalent (SWE) is a measure of liquid water in the snow pack. This information is important in many cases, for example when predicting spring flooding in arctic and subartic regions. The measurement of SWE requires a lot of manual work and multiple samples. Because of this, efficient and accurate forecasts of SWE are crucial to get reliable estimates of SWE to be used in downstream problems (e.g. hydrological modelling). We compared two different recurrent neural network (RNN) architectures: Long short-term memory (LSTM) and gated recurrent unit (GRU) and had commonly used physical model as a baseline. All the models were verified with real data from Finland. We used three test stations Inari, Vaala, and Lohja which had good spatial variability along the north-south axis. Lohja and Inari stations are 975 km apart, Vaala is between these two.

Comparing GRU and LSTM

We wanted the model to be efficient, and tuned the model be as lightweight as possible while maintaining the forecasting accuracy. We compared the GRU and LSTM RNN with hidden state dimension of 8 and 128 (lightweight and heavy). Both had input of temperature, precipitation and history SWE values of 180 days. Lightweight model used two-week weighted mean of the inputs, and thus input length of 12. NSE error metric of RNNs can be seen in Figure 1. Table 1 shows the amount of parameters and required model training time for all model variants.

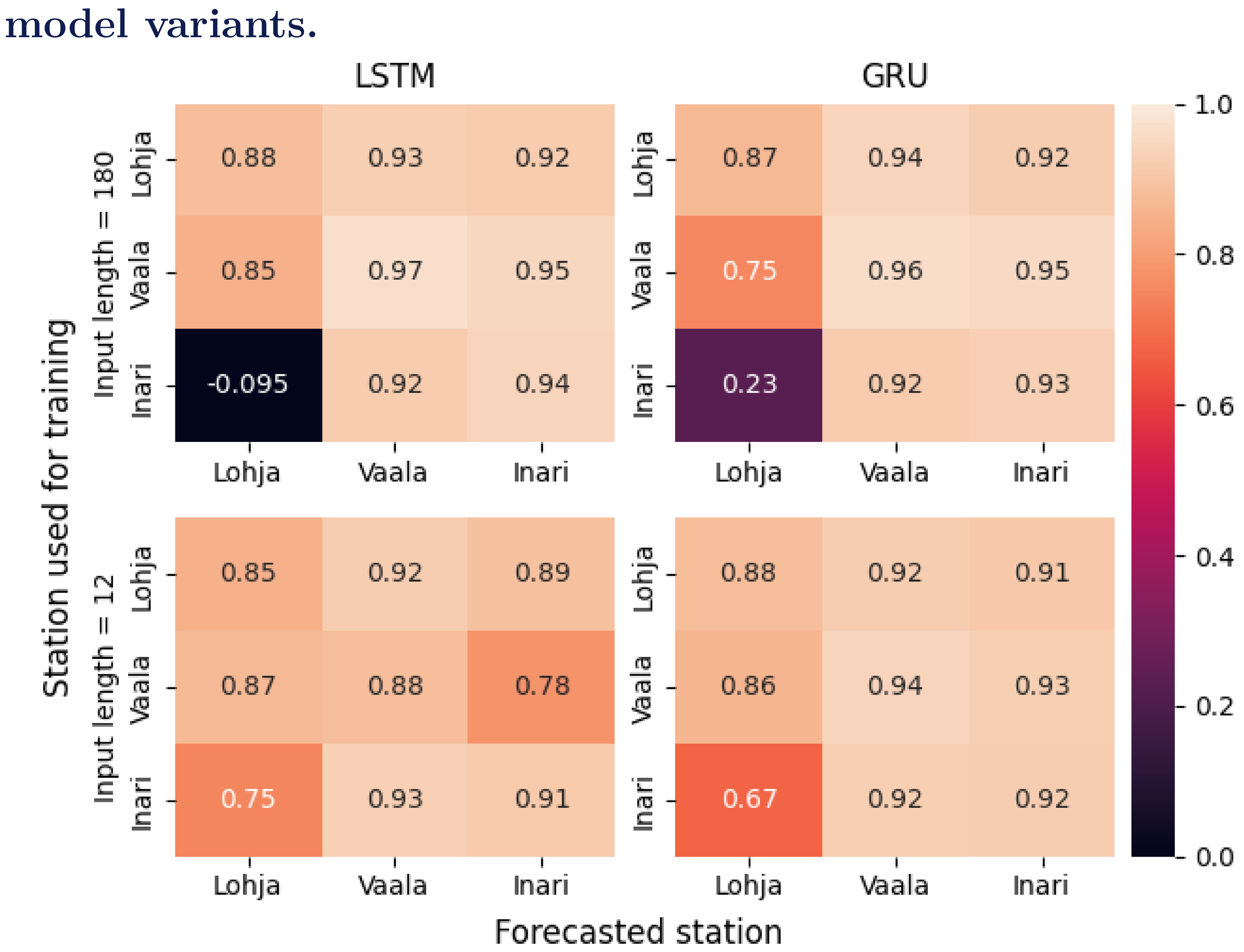

Figure 1:NSE error metric for lightweight and heavy with GRU and LSTM architectures. Single model was trained with data from only one station, and after that the model was evaluated in all of the stations test sets.

Table 1:Number of parameters and training time in seconds for all model variants

	Training time (s)		Parameters	
RNN	Heavy	Lightweight	Heavy	Lightweight
LSTM	1202	30	67713	393
GRU	994	32	51201	321

Enhancing the model further

After finding out that the GRU performs with similar performance in the heavy model model variant, and even better with the lightweight we tried to push the forecasting accuracy even further with GRU. We added time2vec (t2v) layer to the model, and trained the model with data from all stations. We found out that the lightweight model did not benefit either from the extra data from all stations or the added t2v layer. With the heavy model we were able to enhance the average NSE from 0.91 to 0.95. Our proposed model architectures can be seen in Figure 2 together with forecast in Figure 3.

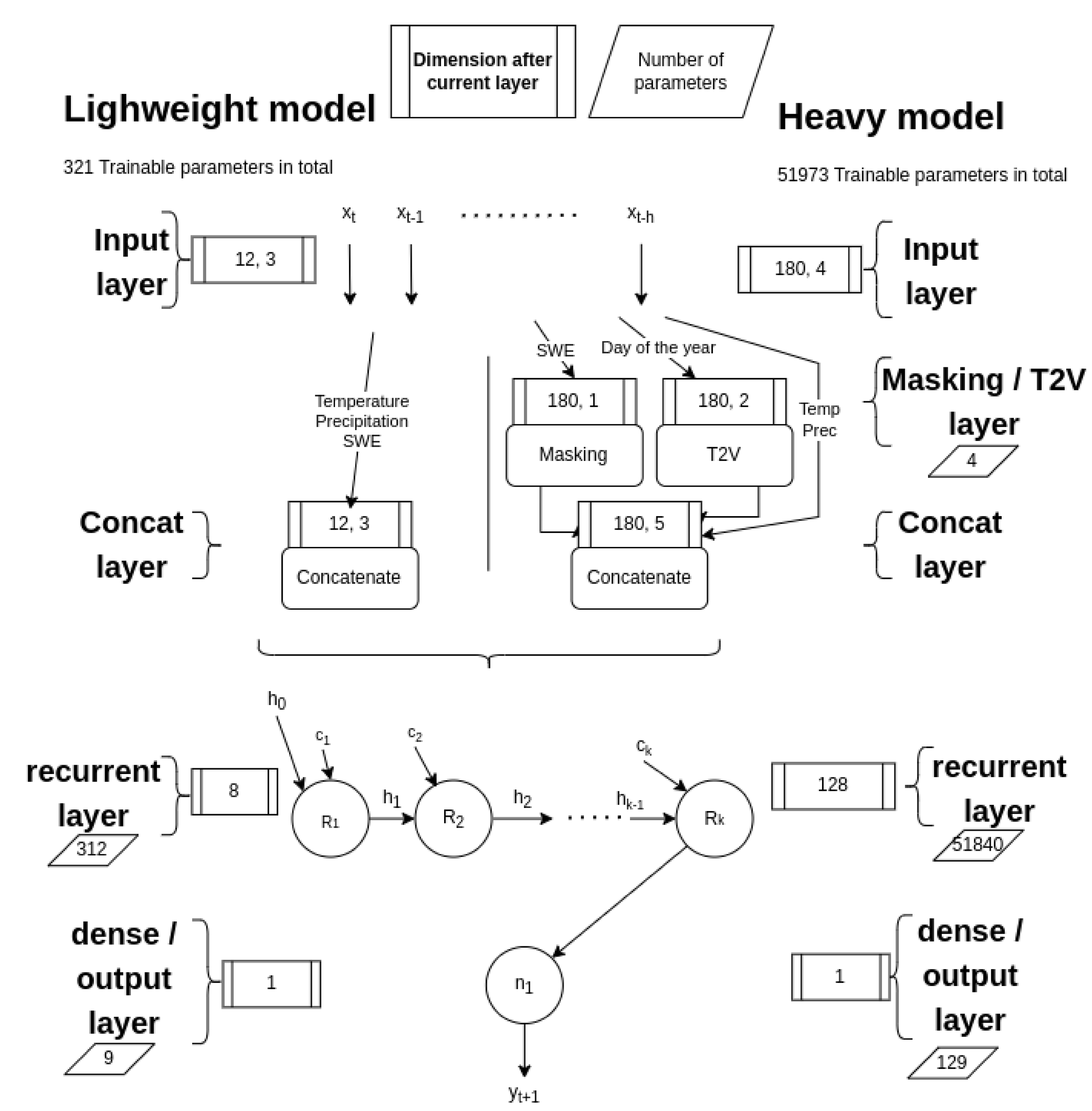

Figure 2:Proposed model architectures.

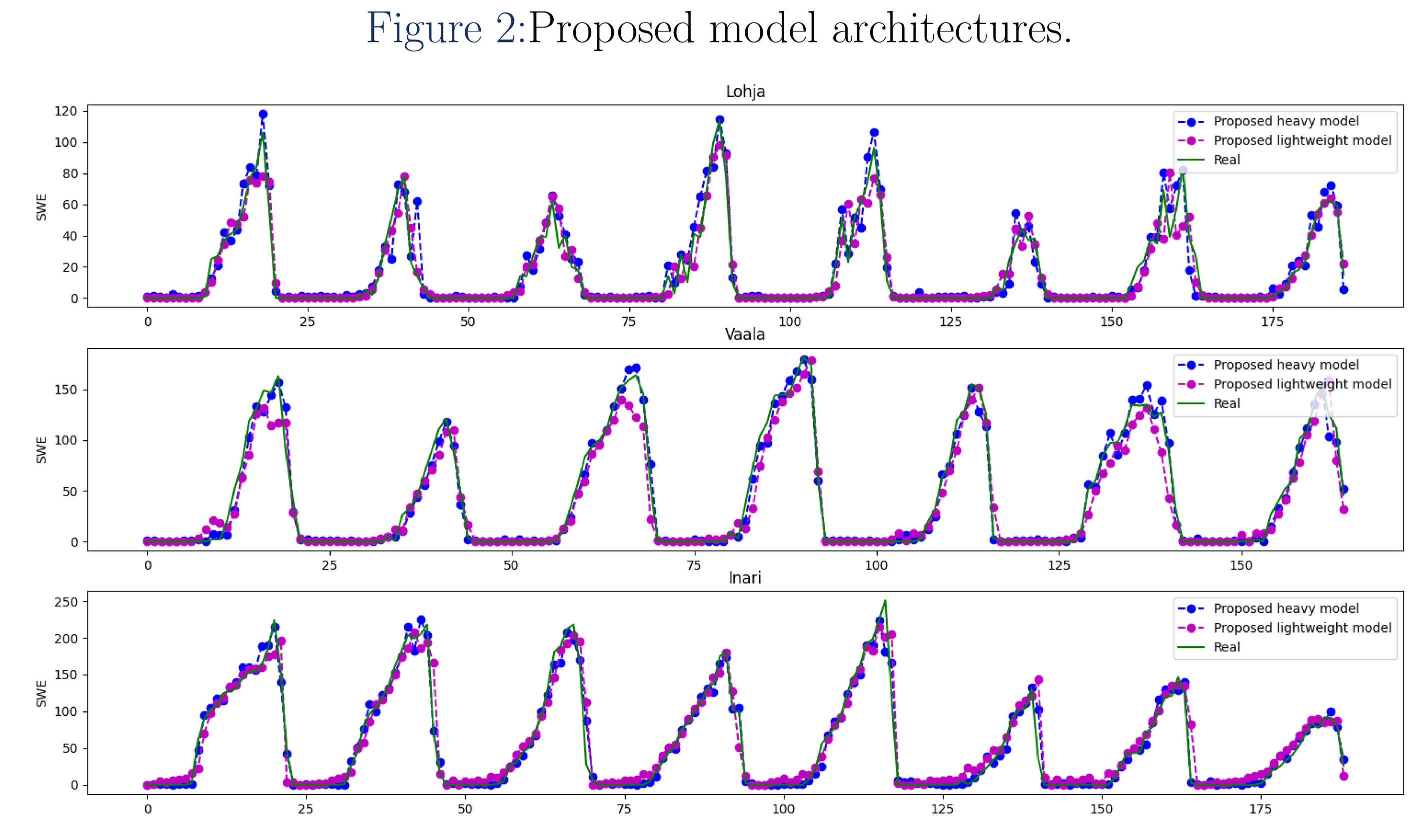

Figure 3:Forecast for the test set of all stations by both proposed models.

Conclusions

We have shown that the RNNs have strong generalization capabilities for SWE forecasting, and that GRU outperforms the LSTM with efficient model architectures. As the outcome we propose two models: a lightweight and heavy model. The commonly used physical model had an average NSE of 0.81. We were able to enhance the forecasting accuracy from this significantly; an average NSE of 0.91 and 0.95 for lightweight and heavy model, respectively.