Mini-Batch Learning Strategies for modeling long term temporal dependencies: A study in environmental applications

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A The investigated base models

Table 1: The settings of base models.

Model	Settings
GRU	1-layer, 32 hidden state size
LSTM	1-layer, 32 hidden state size
Transformer	1-layer, 21 embedding size,7 head numbers, masked multi-head attention

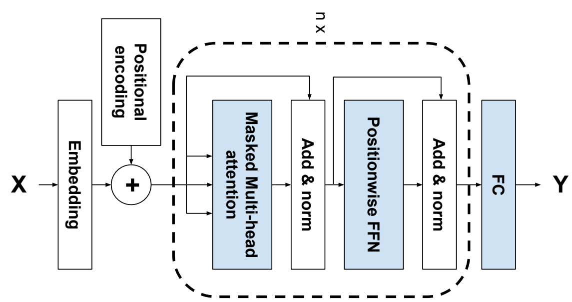

Figure 1: The investigated transformer model [1].

B The additional six watersheds

Table 2: basin characteristics

Basin	state	mean precipitation mm	area gauged km^2	frac_snow %
01162500	MA	3.783534565	49.71	0.226769185
06614800	CO	2.917613963	4.03	0.760476738
12114500	WA	7.241880903	66.56	0.406517039
02300700	FL	3.89649692	73.84	0
11141280	CA	1.883665982	54.01	0.00078778
09066200	CO	2.650229979	16.1	0.712216418

We provide results on six additional basins which span drought, snow, and humid regions across the USA, as table 2 shows.

Figure 2 shows the boxplots of the overall RMSEs from 5 separate runs of the learning strategies on the basins. And Figure 3 are the AvgStepRMSE plots. All figures show that the behaviors of the learning methods are mostly consistent across different basins and conform to the findings in the paper but with few exceptions.

The figure 3 shows all strategies get some abnormal AvgStepRMSE peaks in SF predictions on basin 02300700 at FL and basin 12114500 at WA and in SNO predictions on basin 11141280 at CA. These abnormal peaks happen due to some extremely rare floods and snowstorms. We draw the hydrograph to study these extreme events in figure 4, which reveal the extreme rainstorm and snowstorm make the observations several magnitudes higher than usual. Since such events only happen once in several decades, all strategies underpredict values, so we observe the AvgStepRMSE peaks.

References

[1] Frederik Kratzert et al. Neuralhydrology — a python library for deep learning research in hydrology. *Journal of Open Source Software*, 7(71):4050, 2022.

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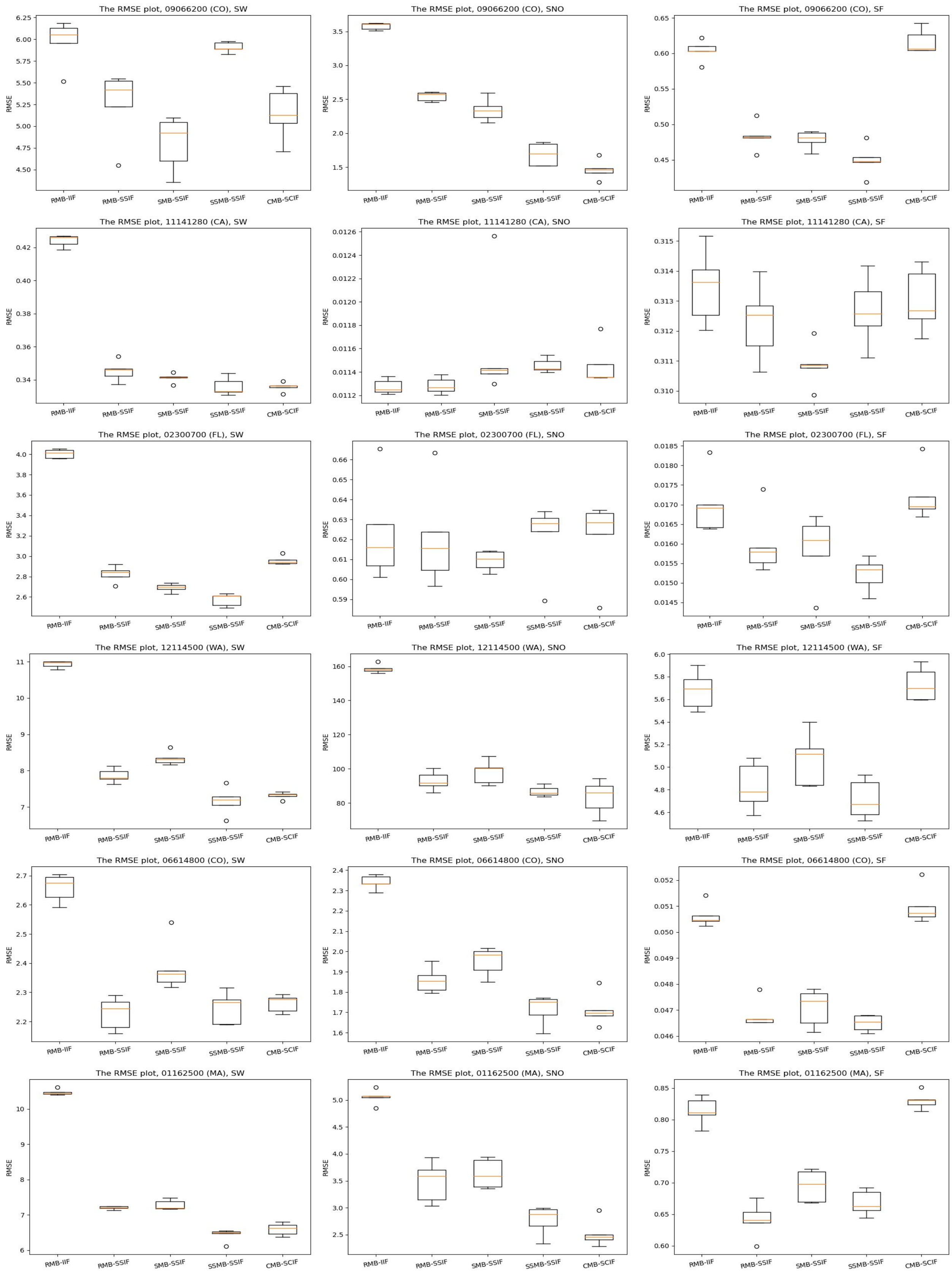

Figure 2: These boxplots draw the overall RMSEs of learning methods on different basins.

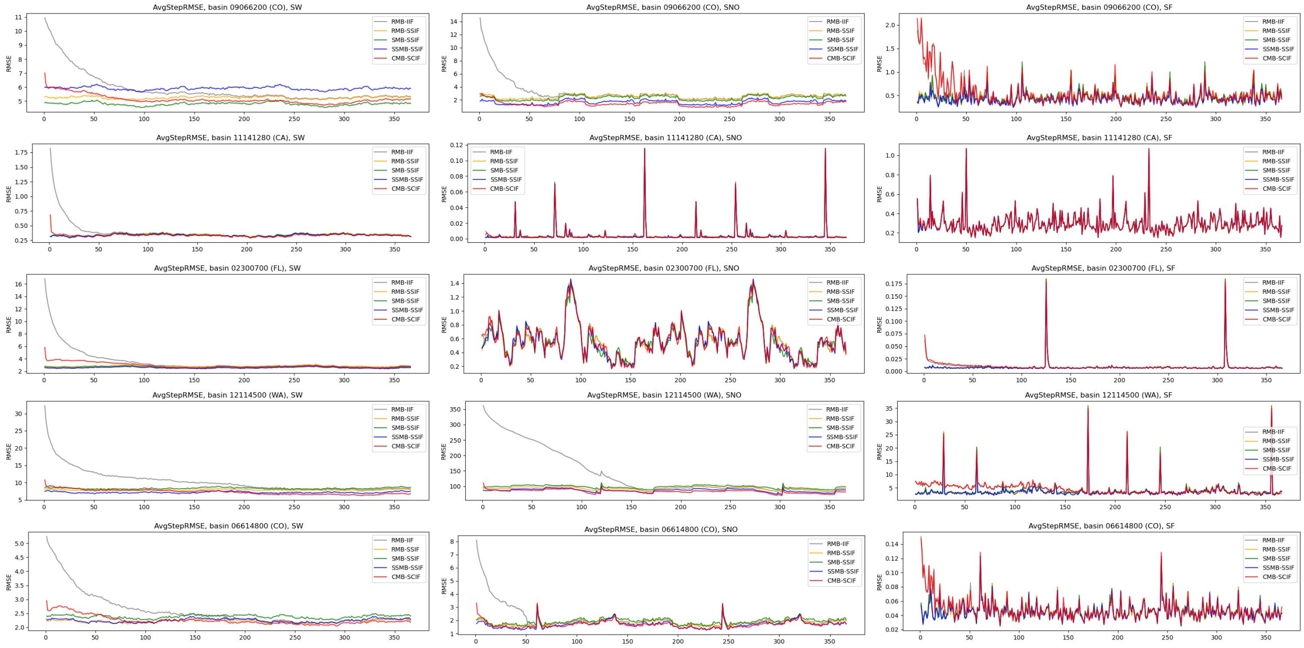

Figure 3: These figure shows the average RMSE at each RNN timestep on testing sets across all different basins.

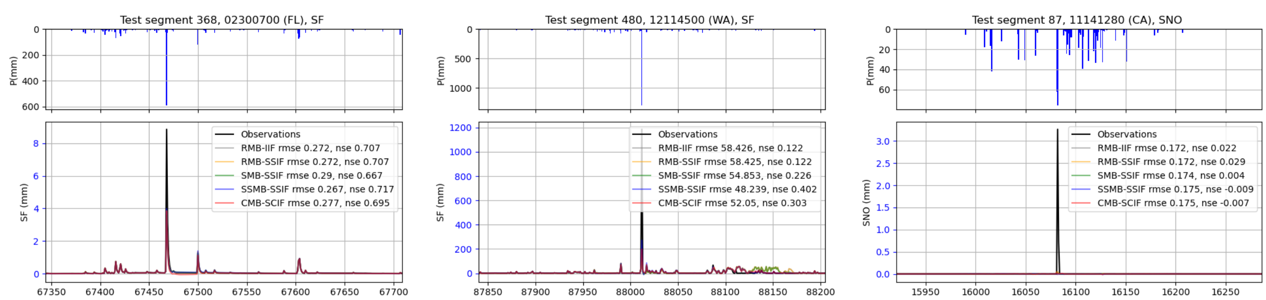

Figure 4: This figure shows three hydrographs. The top plot of the hydrograph draws the precipitation (P); the bottom plot draws the target variables.