Predição das vazões observadas na bacia “Jaguari – Jacareí”com modelos conceituais e redes neurais LSTM

Arlan dos Reis Scortegagna

Professor Luiz Oliveira - PPGInf - UFPR

Trabalhos revisados – Artigo 1

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Rainfall–runoff modelling using Long Short-Term Memory (LSTM) networks

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Principais resultados – Kratzert et al. (2018)

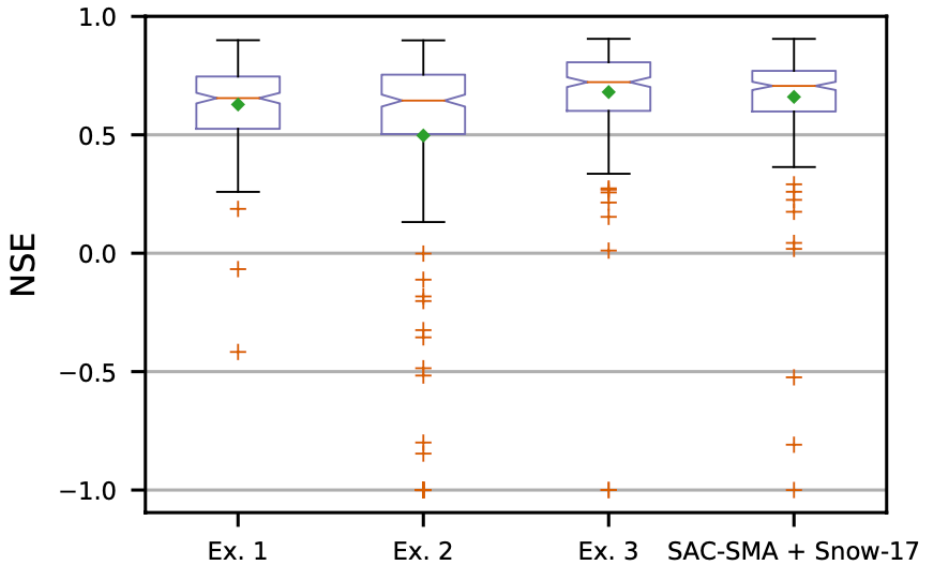

Figure 14. Boxplot of the NSE of the validation period for our three Experiments and the benchmark model. The NSE is capped to −1 for better visualization. The green square diamond marks the mean in addition to the median (red line).

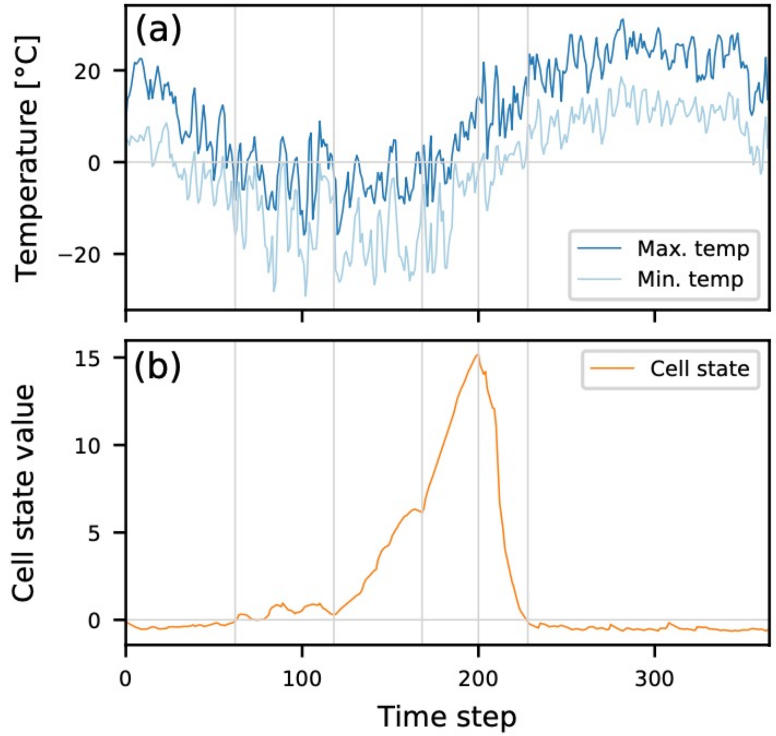

Figure 15. Evolution of a specific cell state in the LSTM **(b)** compared to the daily min and max temperature, with accumulation in winter and depletion in spring **(a)**. The vertical grey lines are included for better guidance.

Trabalhos revisados – Artigo 2

Journal of Hydrology 605 (2022) 127297

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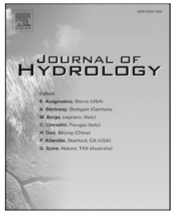

Improving streamflow prediction in the WRF-Hydro model with LSTM networks

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A B S T R A C T

Researchers have attempted to use machine learning algorithms to replace physically based models for streamflow prediction. Although existing studies have contributed to improving machine learning methods, they still have weaknesses, such as large dataset requirements and overfitting. Therefore, we propose an approach that combines the Weather Research and Forecasting hydrological modeling system (WRF-Hydro) and the Long Short-Term Memory (LSTM) network, i.e., WRF-Hydro-LSTM, to improve streamflow simulations. In this approach, LSTM was employed to predict the residual errors of WRF-Hydro; in contrast, the conventional approach with LSTM predicts streamflow directly. Here, we performed numerical experiments to predict the inflow of Soyangho Lake in South Korea using WRF-Hydro-LSTM, WRF-Hydro-only, and LSTM-only. WRF-Hydro-LSTM and LSTM-only showed better results (NSE = 0.95 and R greater than 0.96) compared to WRF-Hydro-only (NSE = 0.72 and R = 0.88); however, in terms of the percent bias, WRF-Hydro-LSTM had a better value (1.75) than LSTM-only (17.36). While the LSTM-only follows objective functions and not physical principles, WRF-Hydro-LSTM simulates residual errors and efficiently decreases uncertainties that are inherent with conventional methods. Furthermore, a sensitivity test on the training dataset indicated that the correlation coefficient and NSE value were not overly sensitive, but the PBIAS value differed substantially depending on the training set. This study demonstrates that WRF-Hydro-LSTM is particularly useful for representing real-world physical constraints and thus can potentially improve streamflow prediction compared to using either of the two approaches exclusively.

Principais resultados – Cho e Kim (2022)

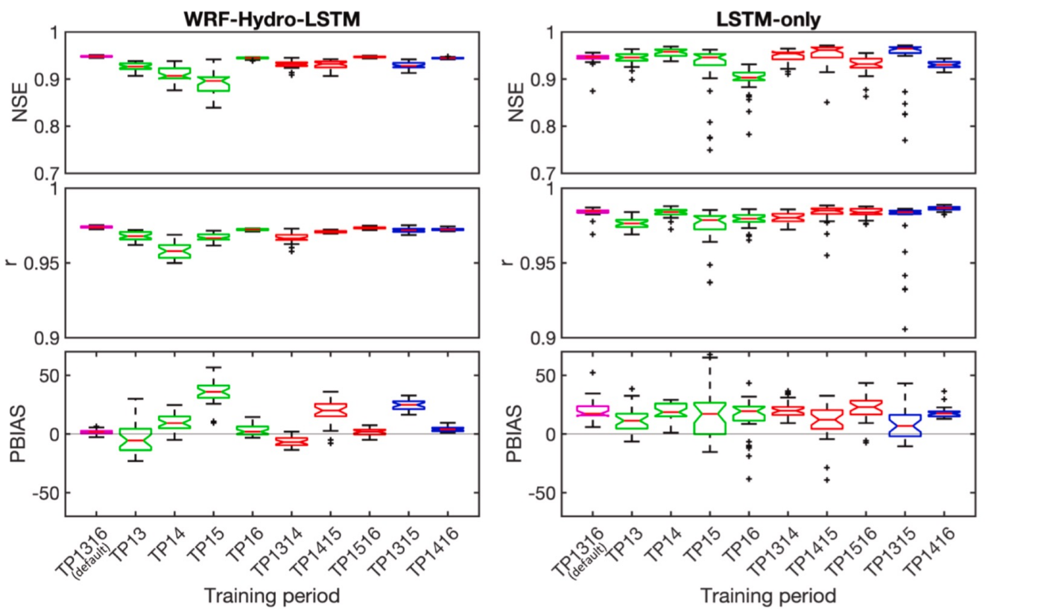

Fig. 8. Comparisons among the different training periods (TP) cases (1, 2, 3, and 4 years between 2013 and 2016) with their optimized combination of hyper-parameters (30 iterations per case).

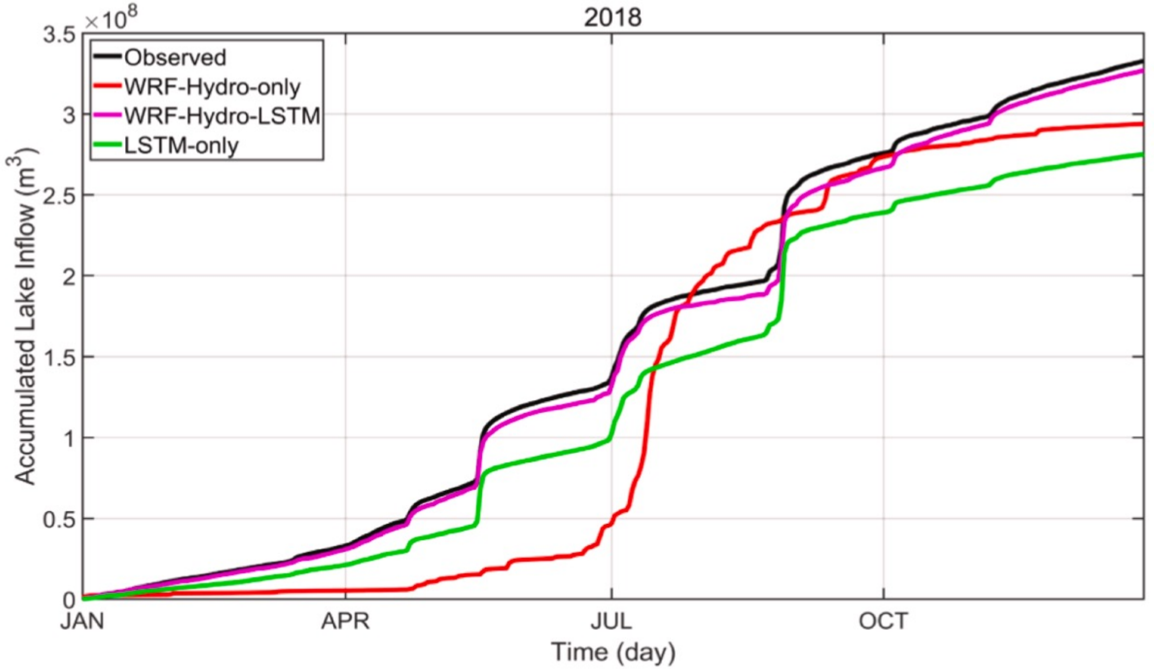

Fig. 6. Comparison of the cumulative lake inflow between the simulations and observations.

Outros trabalhos...

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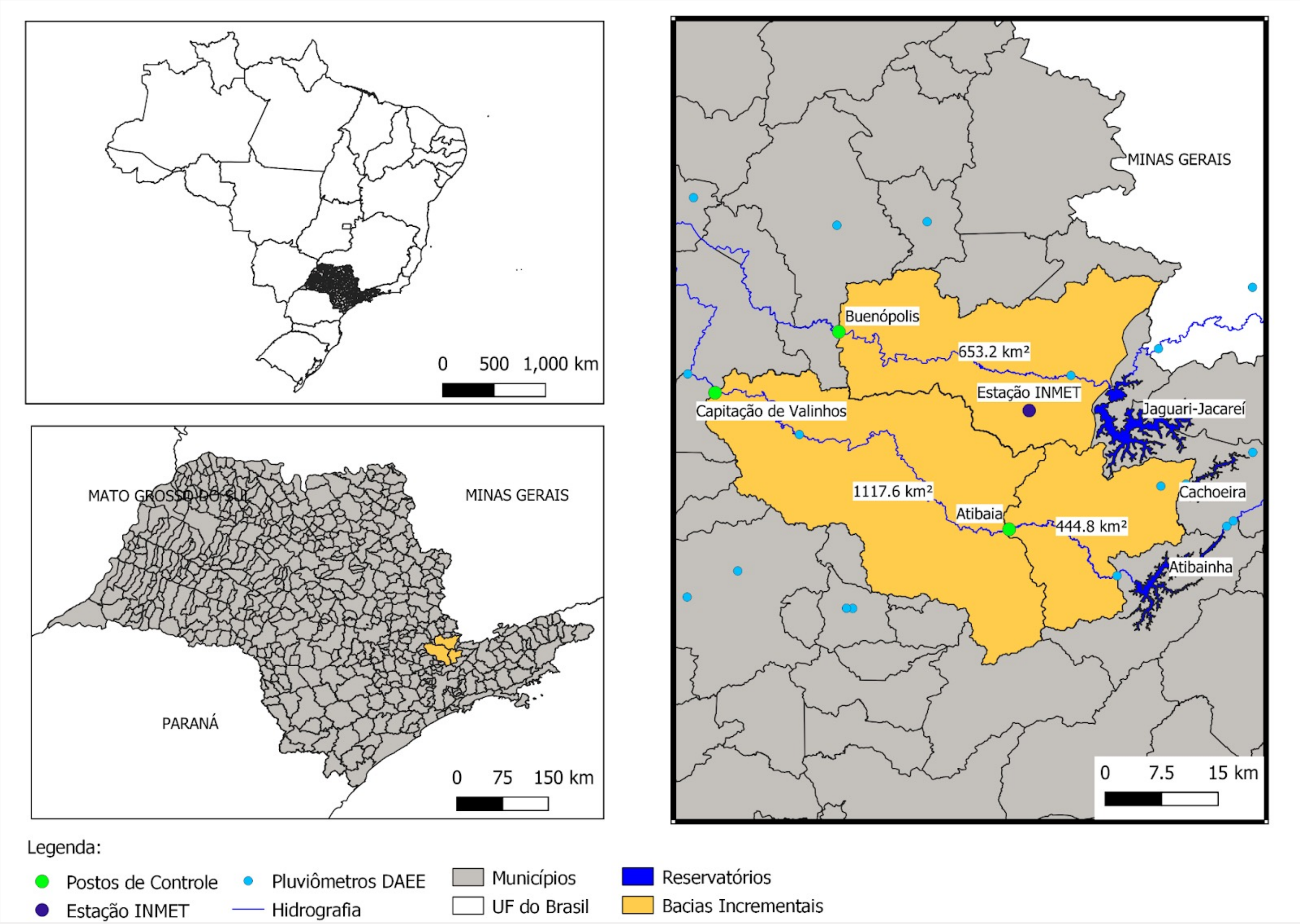
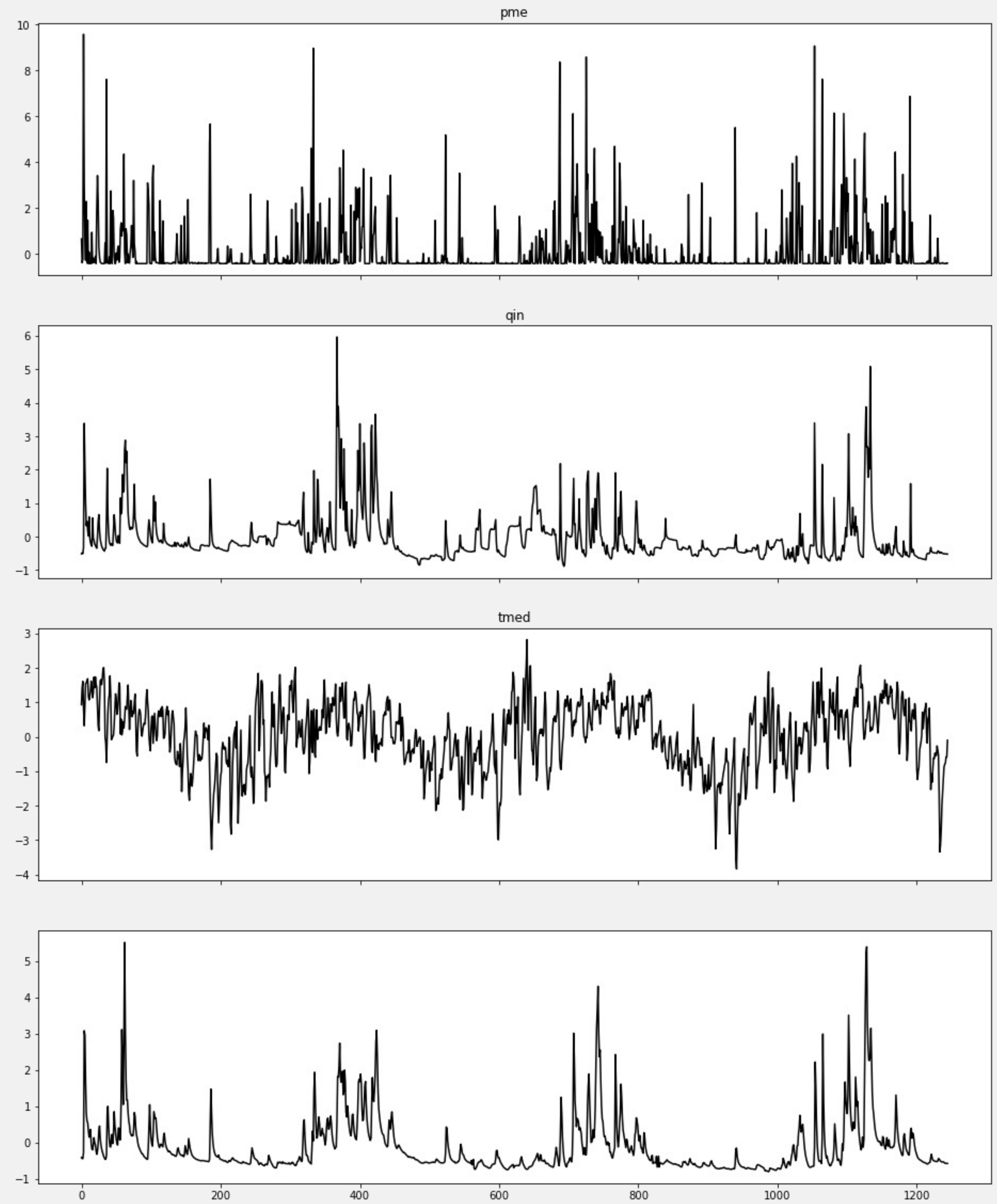
Dados


0 500 1,000 km
MATO GROSSO DO SUL
MINAS GERAIS
PARANÁ
0 75 150 km
MINAS GERAIS
Buenópolis
653.2 km²
Estação INMET
Capitação de Valinhos
Jaguari-Jacareí
1117.6 km²
Cachoeira
Atibaia
444.8 km²
Atibainha
0 7.5 15 km
Legenda:
Postos de Controle
Estação INMET
Pluviômetros DAEE
Hidrografia
Municípios
UF do Brasil
Reservatórios
Bacias Incrementais

Dados



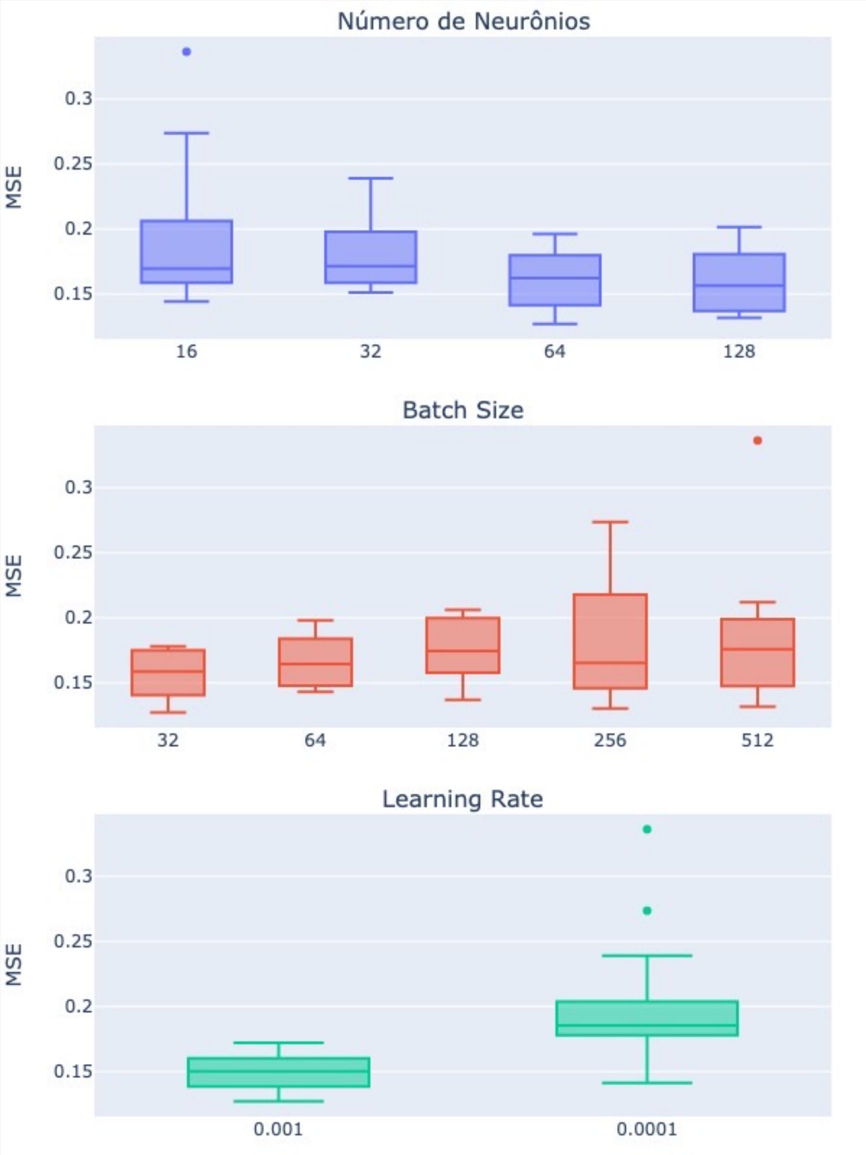
Experimentos

- *SAC-SMA-only* (trabalho anterior)
- *LSTM-Only*
- *SAC-SMA-LSTM*

Resultados – Avaliação de Sensibilidade

- *LSTM-only*

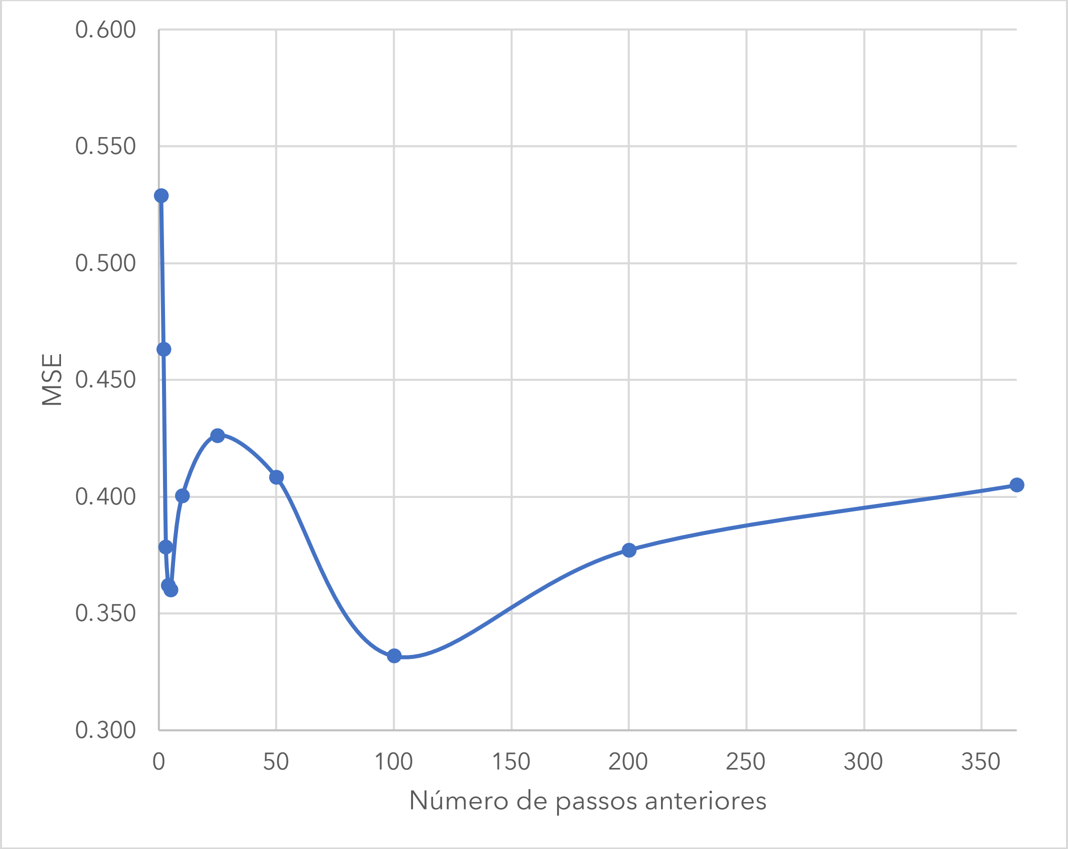
#	N	BS	LR	min_loss	min_epoch	#	N	BS	LR	min_loss	min_epoch
1	16	32	0.001	0.159	5	**21**	64	32	0.001	0.127	5
2	16	32	0.0001	0.178	59	**22**	64	32	0.0001	0.141	52
3	16	64	0.001	0.144	23	**23**	64	64	0.001	0.156	8
4	16	64	0.0001	0.185	97	**24**	64	64	0.0001	0.173	18
5	16	128	0.001	0.161	14	**25**	64	128	0.001	0.169	8
6	16	128	0.0001	0.206	65	**26**	64	128	0.0001	0.180	50
7	16	256	0.001	0.160	21	**27**	64	256	0.001	0.130	57
8	16	256	0.0001	0.274	97	**28**	64	256	0.0001	0.196	88
9	16	512	0.001	0.149	35	**29**	64	512	0.001	0.146	12
10	16	512	0.0001	0.336	99	**30**	64	512	0.0001	0.186	98
11	32	32	0.001	0.172	4	**31**	128	32	0.001	0.140	15
12	32	32	0.0001	0.159	23	**32**	128	32	0.0001	0.178	19
13	32	64	0.001	0.151	5	**33**	128	64	0.001	0.143	4
14	32	64	0.0001	0.182	70	**34**	128	64	0.0001	0.198	37
15	32	128	0.001	0.154	7	**35**	128	128	0.001	0.137	2
16	32	128	0.0001	0.198	71	**36**	128	128	0.0001	0.201	76
17	32	256	0.001	0.161	11	**37**	128	256	0.001	0.132	9
18	32	256	0.0001	0.239	66	**38**	128	256	0.0001	0.170	84
19	32	512	0.001	0.171	30	**39**	128	512	0.001	0.132	13
20	32	512	0.0001	0.212	99	**40**	128	512	0.0001	0.181	70



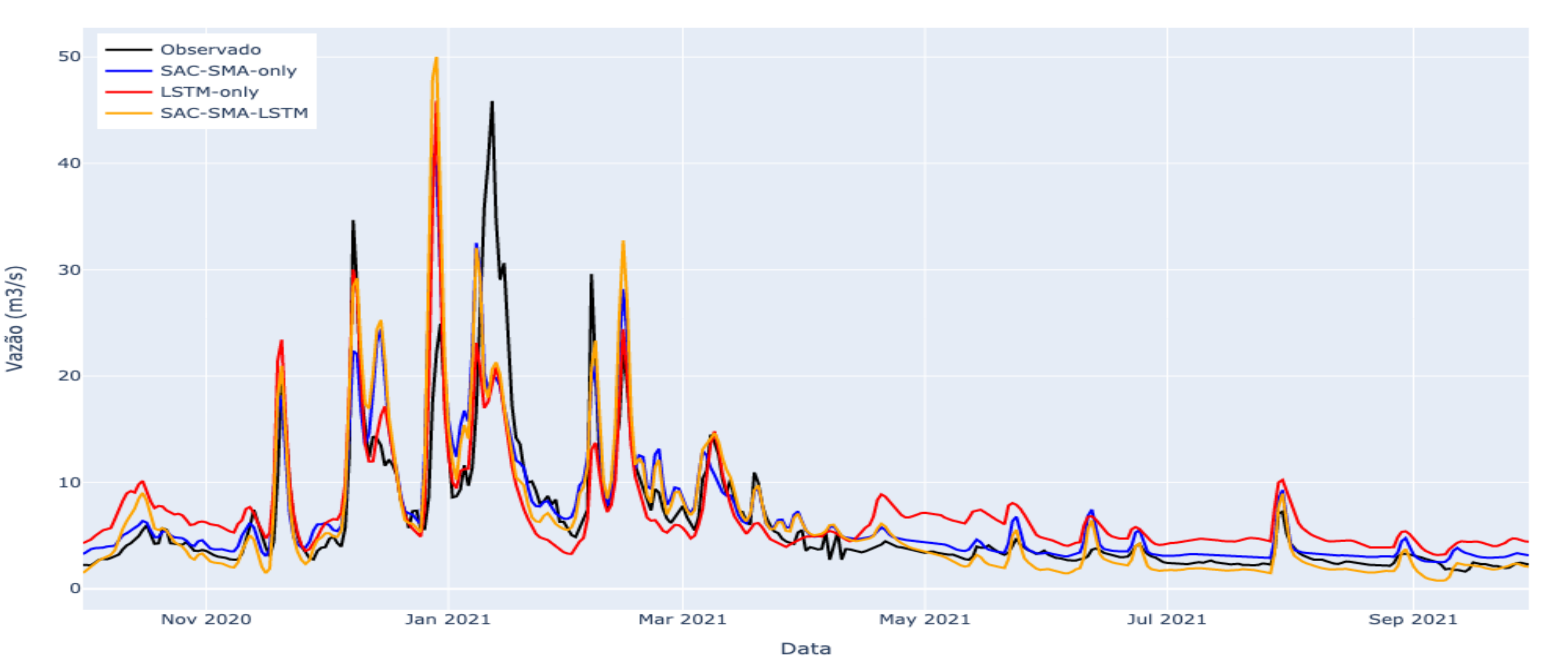
Resultados – Avaliação de Sensibilidade

- *SAC-SMA-LSTM*

#	n_passos	min_loss	min_epoch
1	1	0.529	41
2	2	0.463	16
3	3	0.379	39
4	4	0.362	9
5	5	0.360	21
6	10	0.400	19
7	25	0.426	4
8	50	0.408	1
9	100	0.332	7
10	200	0.377	10
11	365	0.405	1



Hidrograma – Ano hidrológico (out/2020 – set/2021)



Próximos passos...

- Todas as bacias do Cantareira ao mesmo tempo ?
- Aplicação no CAMELS-BR
- Aplicação no InfoHidro
- One-shot forecasts

Ainda restam dúvidas...