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Comment on hess-2022-295

Anonymous Referee #2

Referee comment on "Continuous streamflow prediction in ungauged basins: long short-term memory neural networks clearly outperform traditional hydrological models" by Richard Arsenault et al., Hydrol. Earth Syst. Sci. Discuss., https://doi.org/10.5194/hess-2022-295-RC2, 2022

General comments

This manuscript is a positive addition to the growing amount of research on the use of machine learning techniques in hydrological modelling with a focus on ungauged basins. The study compares an LSTM-based model trained over multiple catchments with three traditional hydrological models calibrated using several regionalization methods. Overall, the LSTM outperformed the traditional hydrological models at almost all catchments regardless of regionalization method used. This manuscript provides interesting results, is well structured, and was enjoyable to read. However, some additional clarifications throughout the manuscript would allow the reader to fully understand the chosen methodology and the presented results. Please see the specific comments below.

Specific comments

Introduction: As the authors rightly point out the LSTM has been used in several studies in recent years. However, the literature review is mainly focused on work conducted on catchments in North America and with limited acknowledgment of studies conducted in other regions (e.g., Choi et al., 2022; Nogueira Filho et al., 2022; Ayzel et al., 2021; Ayzel et al., 2020). Additionally, it would be beneficial to include a couple of lines near the beginning explaining that this study uses regionalization of hydrological model parameters specifically, and briefly defining what is meant by “hydrological model”.

Line 210-212: I am confused by the sentence “Each of these models was calibrated using the Covariance Matrix Adaptation Evolution Strategy (CMAES; Hansen et al., 2003) optimization algorithm in the Arsenault and Brissette (2014) study, and parameters are reused here to maintain the comparability to this study.” Was the HSAMI model not the only hydrological model used in the Arsenault and Brissette (2014)? Please clarify which parameters are reused, and how they relate to the calibration method and results described in lines 210-225.

Line 262: Why was N=5 chosen (over other values between 4-8)? Please state the reasoning.

Line 275: Please state how many catchments were classified as “poor” and thus removed when the filter was applied.

Line 307-308: “The twelve static descriptors presented in Table 1 allow the model to distinguish between each catchment.”. Highlighting these variables in Table 1 may make it easier to understand which 12 are used as input to the LSTM. Also land cover (%) is split into 7 entries in Table 1 but I think is only considered as 1 of the 12 static descriptors which is confusing.

Line 312: Please clearly define the training, validation, and testing catchments.

Line 330: Why was model #7 chosen as the LSTM structure of choice? Please state the reasoning.

Line 374-375: Were non-linear relationships between catchment descriptors and NSE values considered?

Line 395-396: “relatively simple LSTM model”. Is this still referring to model #7 which is the most complex of the LSTM models tested? Please clarify. Also, on line 489 - “simple LSTM model”.

Lines 455-459: As discussed in the introduction (lines 119-126) traditional hydrological models and LSTM models show different behaviours in terms of performance for increasing lengths of data (e.g., the plateauing after 3 years of the GR4J model (line 122)). Please comment on the “fair-ness” of the comparison considering only catchments with at least 30 years of data are included?

Technical corrections

Line 12: Suggest changing “A series of …” to “a set of …” as series implies that there is a sequential element to the methods.

Line 12: “regionalization methods are applied”

Line 180-181: “Environment and Climate Change Canada (ECCC), and the United States Geological Survey (USGS).”

Line 232: Suggest changing “for each scenario” to “for each of the 18 scenarios” for clarity.

Line 288: “have difficulty remembering”

Line 315: “then converted from m.s^{-1} to mm.d^{-1}” (as the division by drainage area would already have removed two spatial dimensions).

References

Choi, J., Lee, J., & Kim, S. (2022). Utilization of the Long Short-Term Memory network for predicting streamflow in ungauged basins in Korea. *Ecological Engineering*, *182*, 106699.

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Ayzel G, Kurochkina L, Abramov D, Zhuravlev S. Development of a Regional Gridded Runoff Dataset Using Long Short-Term Memory (LSTM) Networks. Hydrology. 2021; 8(1):6. https://doi.org/10.3390/hydrology8010006

Ayzel, G., Kurochkina, L., Kazakov, E., & Zhuravlev, S. (2020). Streamflow prediction in ungauged basins: benchmarking the efficiency of deep learning. In E3S Web of Conferences (Vol. 163, p. 01001). EDP Sciences.