Using LSTMs for Climate Change assessment studies on droughts and floods

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Abstract. Climate change affects occurrences of floods and droughts worldwide. However, predicting climate impacts over individual watersheds is difficult, primarily because accurate hydrological forecasts require models that are calibrated to past data.
We use a large-scale LSTM-based modeling approach that learns a diversity of hydrological behaviors. Previous work shows that this model is more accurate than current state-of-the-art models. This even holds when the LSTM-based approach operates out-of-sample and the current models in-sample.
In this work, we present how this model can assess the sensitivity of the underlying systems with regard to extreme (high and low) flows in individual watersheds over the continental US.

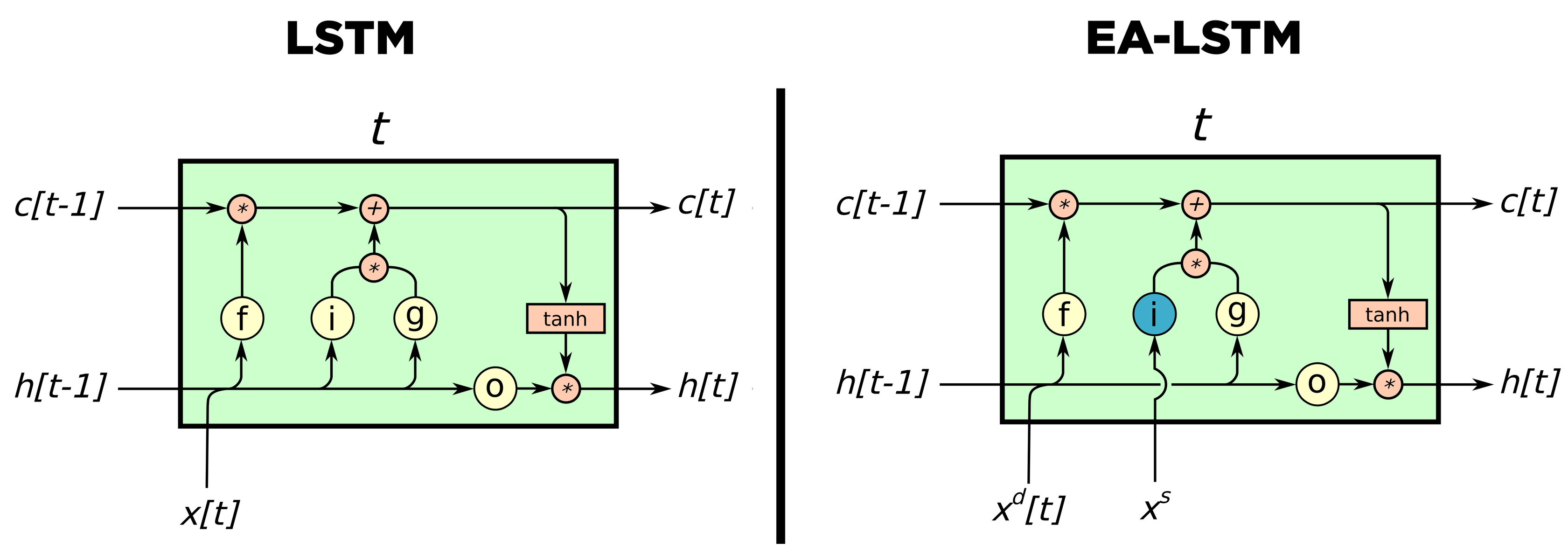

Figure 1. Conceptual diagram of the standard LSTM cell (left) and the adapted EA-LSTM (right).

Method. We use the **Entity-Aware LSTM** (**EA-LSTM**, Fig. 1) where static and dynamic input features are used explicitly for different purposes [1].

$$
\begin{aligned}
\boldsymbol{i} &= \sigma(\boldsymbol{W}_i \boldsymbol{x}_s + \boldsymbol{b}_i) \\
\boldsymbol{f}[t] &= \sigma(\boldsymbol{W}_f \boldsymbol{x}_d[t] + \boldsymbol{U}_f \boldsymbol{h}[t-1] + \boldsymbol{b}_f) \\
\boldsymbol{g}[t] &= \tanh(\boldsymbol{W}_g \boldsymbol{x}_d[t] + \boldsymbol{U}_g \boldsymbol{h}[t-1] + \boldsymbol{b}_g) \\
\boldsymbol{o}[t] &= \sigma(\boldsymbol{W}_o \boldsymbol{x}_d[t] + \boldsymbol{U}_o \boldsymbol{h}[t-1] + \boldsymbol{b}_o) \\
\boldsymbol{c}[t] &= \boldsymbol{f}[t] \odot \boldsymbol{c}[t-1] + \boldsymbol{i} \odot \boldsymbol{g}[t] \\
\boldsymbol{h}[t] &= \boldsymbol{o}[t] \odot \tanh(\boldsymbol{c}[t])
\end{aligned}
$$

Here $\boldsymbol{x}_s$ are static input features (watershed characteristics) and $\boldsymbol{x}_d$ are dynamic inputs (meteorological forcings). Compared to the standard LSTM, the input gate $\boldsymbol{i}$ is static and only controlled by $\boldsymbol{x}_s$, while all remaining parts of the EA-LSTM are controlled by $\boldsymbol{x}_d$ and the recurrent inputs ($\boldsymbol{h}[t-1]$). A single linear layer is used to calculate the network prediction from the hidden state at the last time step.
For a detailed model description as well as an extensive benchmarking, check [1].

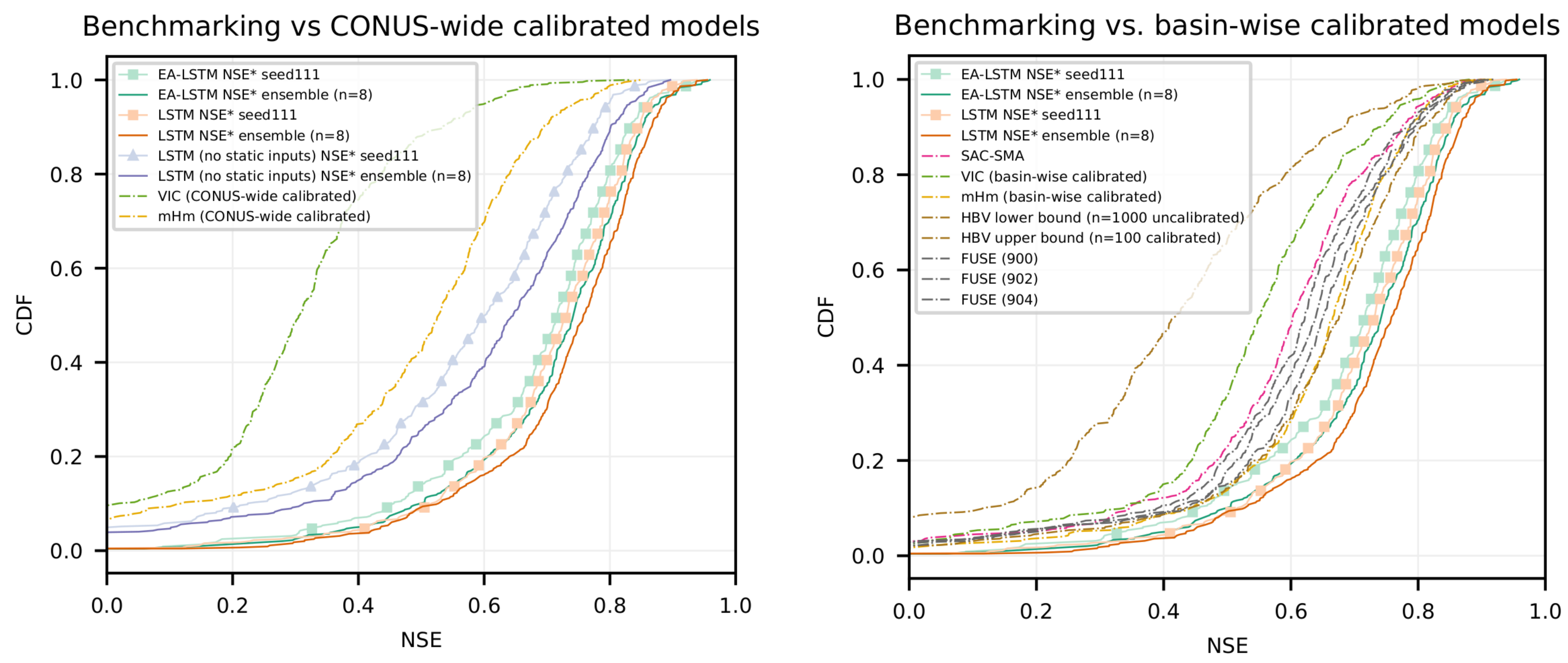

Figure 2. Empirical CDF showing the benchmarking results of our LSTM-based model approach vs. various (state-of-the-art) well-established hydrological models. Left: Compared to regionally calibrated models. Right: Compared to basin-wise calibrated models. The Nash-Sutcliffe Efficiency (NSE) equals the R^2 between observed and simulated runoff. Results are taken from [1].

Data. We used a pre-trained model, released by [1], trained on the publicly available CAMELS data set (Fig. 2). CAMELS consists of 671 natural watersheds across the CONUS, containing meteorological forcings, observed discharge and static watershed attributes [2].
To assess the climate sensitivity of the trained model the method of Morris is used. Concretely, we calculate the gradients of the network prediction w.r.t. $\boldsymbol{x}_s$ for each day in the test period and average the absolute gradients once for flood periods (discharge > 95^{th} percentile) and once for drough periods (discharge < 5^{th} percentile).

Results. By learning simultaneously from a large number of basins under different eco-hydrological regimes, the EA-LSTM can assess influences of different types of boundary conditions, and has the potential to adapt to changing hydrologic or climatic conditions. Overall, our results suggest that low-flow periods (as proxy for droughts) could be more sensitive to changes in climate (Fig. 3).

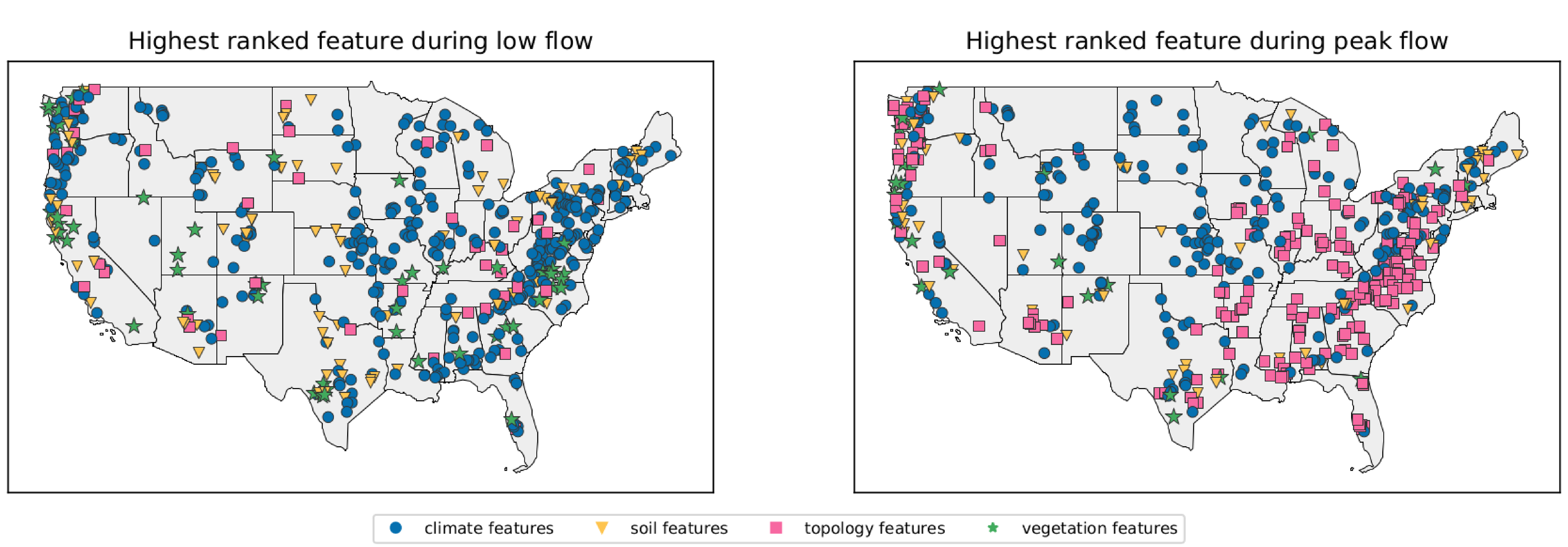

Figure 3. Highest ranked feature for low flow periods on the left-hand side and floods on the right hand-side. The features were grouped into either climate-, soil-, topology-, or vegetation-type feature.

Outlook. Currently, the used basin and climate characteristics are derived once for the entire data period. However the model structure allows for dynamic input features (e.g., dynamic climate and vegetation indexes, or dynamic anthropogenic demand indexes). Feeding the model with evolving input features, e.g. as obtained from climate projections, could make it possible to account for changes to individual basins by building on experience that is learned from modeling the diverse training data set.
This opens the door to fundamentally new possibilities for large-scale hydrological impact assessment under climate change, that is able to maintain its local relevance.

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References.

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[2] Newman, A., Sampson, K., Clark, M.P., Bock, A., Viger, R. J., Blodgett, D.: A large-sample watershed-scale hydrometeorological dataset for the contiguous USA. Boulder, CO: UCAR/NCAR, 2014