

Towards deep learning based flood forecasting for ungauged basins



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[Link](#) to the abstract

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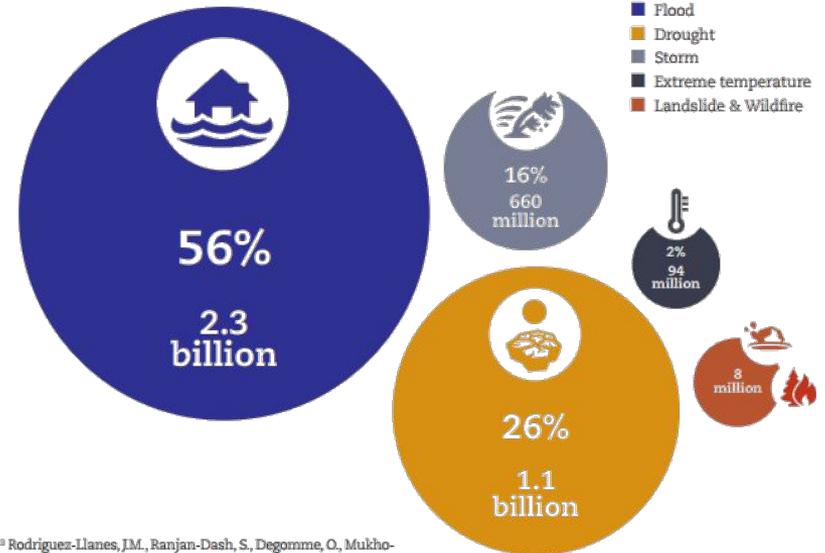
Sepp
Hochreiter 

Introduction

Flood impacts



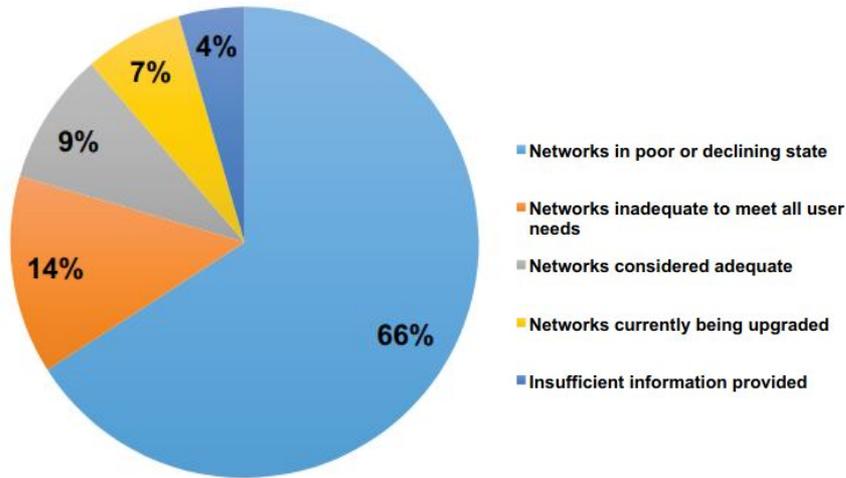
Numbers of people affected by weather-related disasters (1995-2015)
(NB: deaths are excluded from the total affected.)



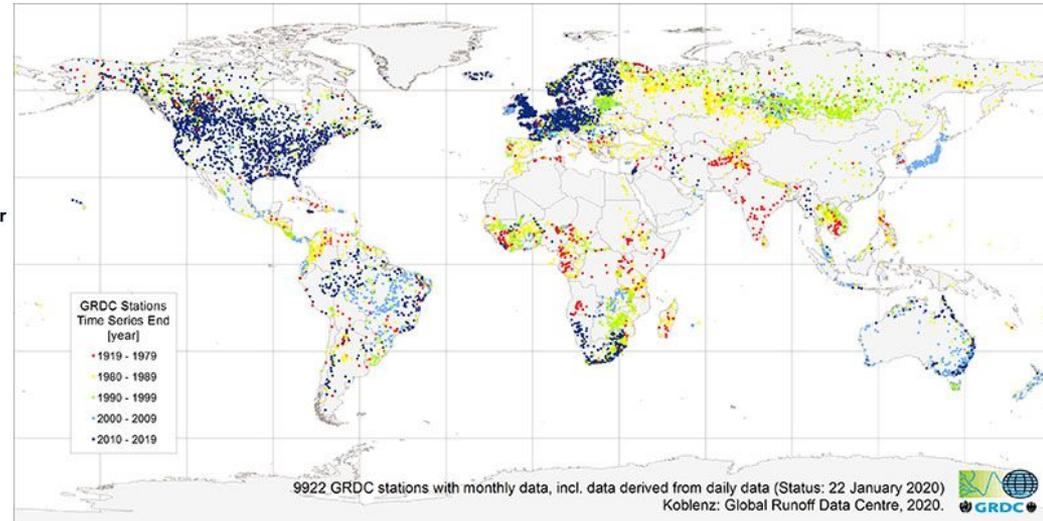
² Rodriguez-Llanes, JM, Ranjan-Dash, S, Degomme, O, Mukhopadhyay, A, Guha-Sapir, D (2011). "Child malnutrition and recurrent flooding in rural eastern India: a community-based survey". *BMJ Open* 2011;1: e000109.

Connection to PUB

Status of Hydrometeorological Observation Networks in Developing Countries



Source: [Worldbank \(2018\)](#)



Only few gauge stations exist throughout low income and developing countries out of which the majority is in a poor or declining state. This makes traditional hydrological modeling difficult, since no gauge records exist for many places to calibrate a streamflow model. Thus, providing streamflow forecasts often translates to prediction in ungauged basins.

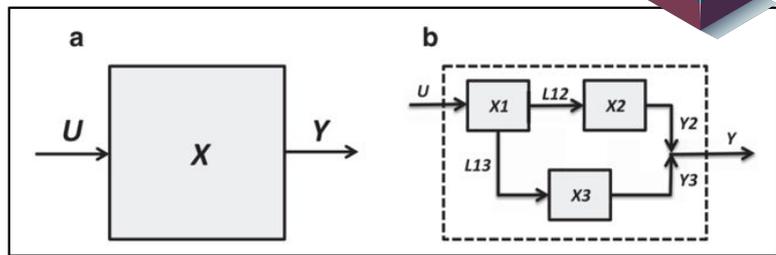
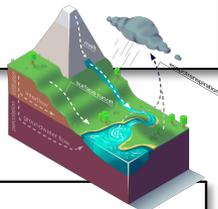
Deep Learning based Rainfall-Runoff Modeling

Similarity of LSTMs & conceptual models

State space model:

$$\mathbf{S}[t] = f(\mathbf{I}[t], \mathbf{S}[t-1]; \Theta_i)$$

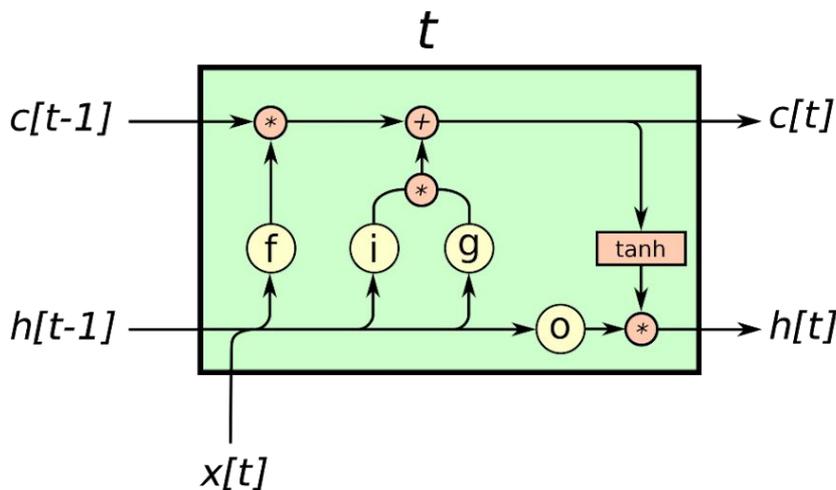
$$\mathbf{O}[t] = g(\mathbf{S}[t]; \Theta_j)$$



LSTM model:

$$\{\mathbf{c}[t], \mathbf{h}[t]\} = f(\mathbf{x}[t], \mathbf{c}[t-1], \mathbf{h}[t-1]; \theta_i)$$

$$\hat{y}[t] = g(\mathbf{h}[t]; \theta_j)$$



Experimental setup

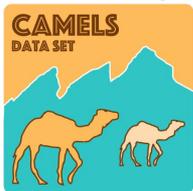
Hundreds of basins

Catchment attributes



+

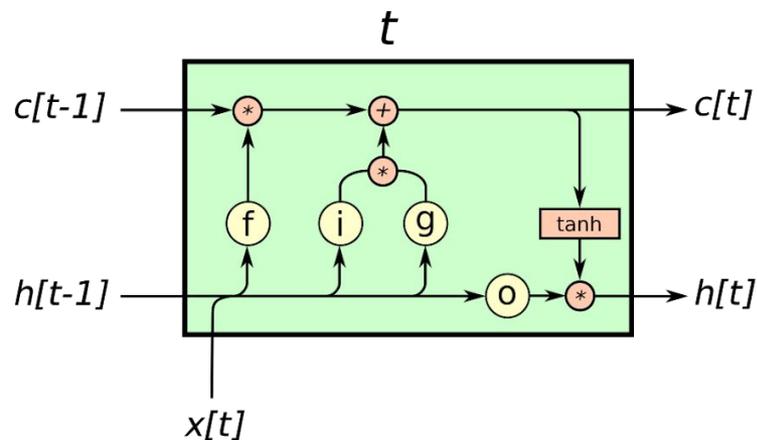
Meteo. Forcings



x n years



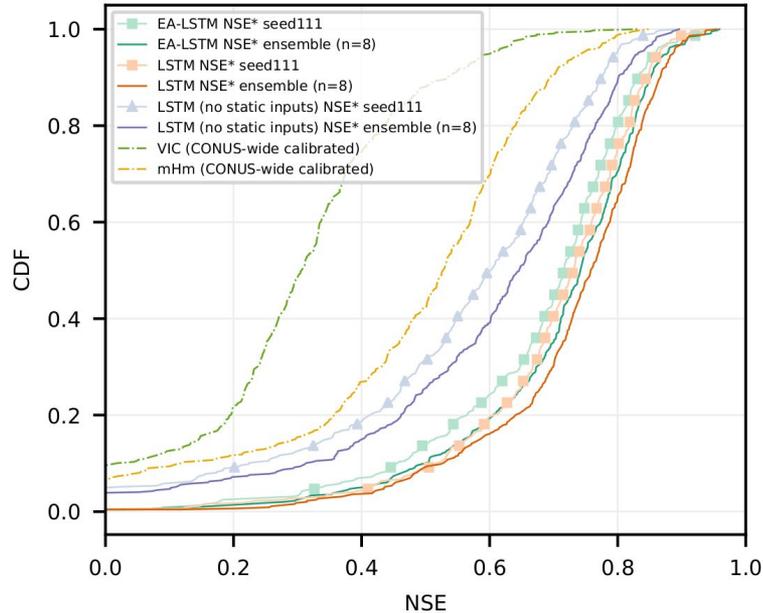
Single
LSTM-based
model



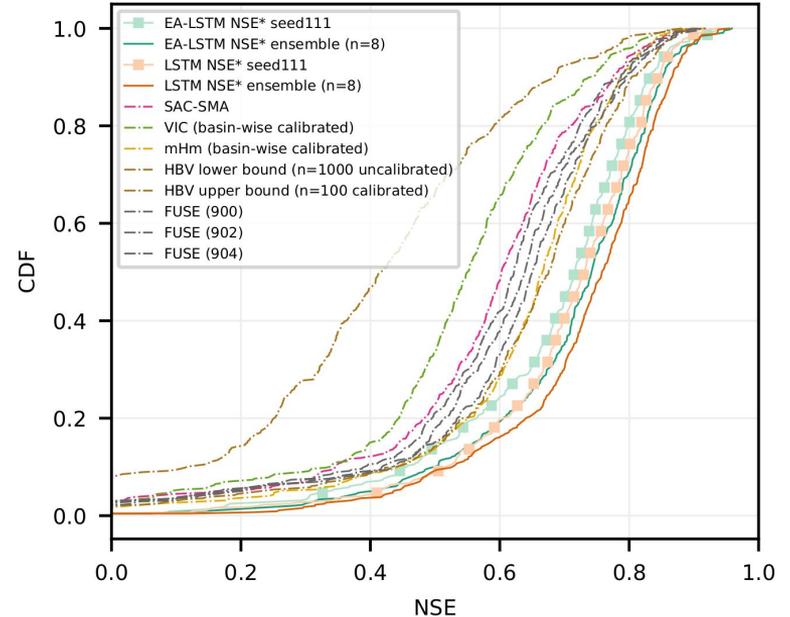
A single LSTM is trained on data of hundreds of basins, using meteorological inputs (no streamflow!) and static catchment attributes.

Benchmarking - gauged

Compared to regional models



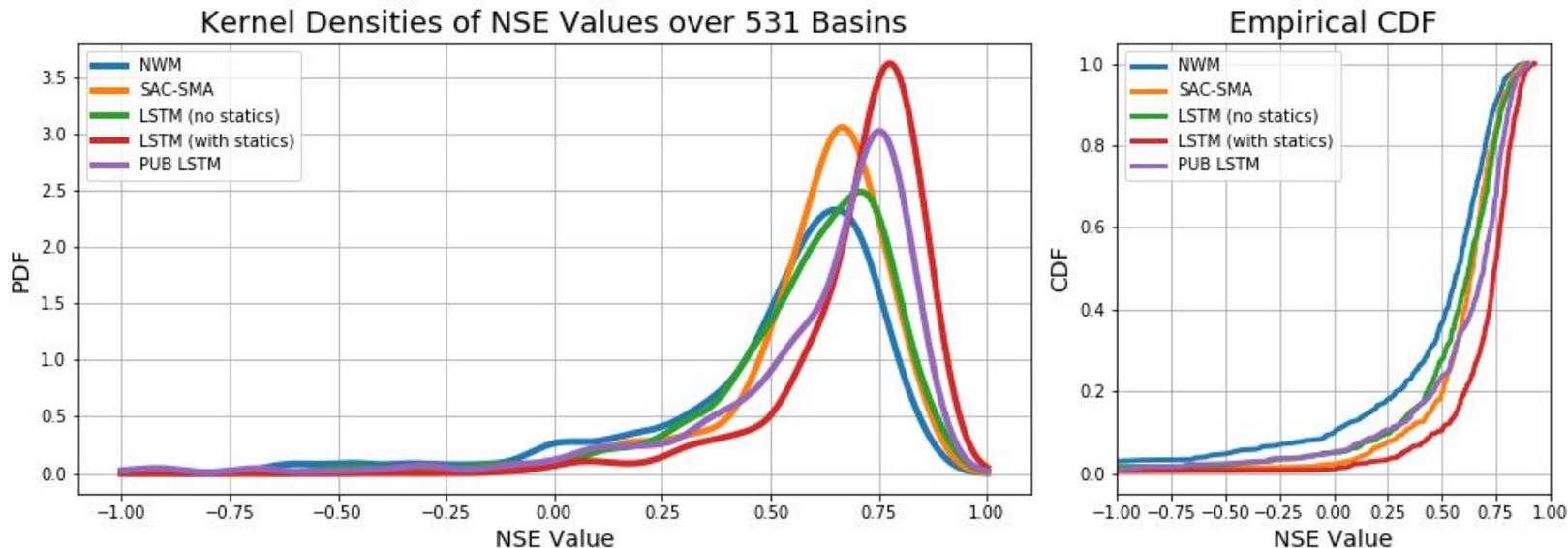
Compared to basin models



In [Kratzert et al. \(2019a\)](#) we benchmarked the LSTM in the *gauged* setting against a bunch of conceptual hydrology models. All are trained on the same forcings and training periods. We compared against models that were regionally optimized (left), and against models that are optimized per-basin (right). Compared to both types of models, our LSTM based models (EA-LSTM & LSTM) outperformed all models by a far margin (evaluated over 447 commonly modeled basins).

That is, a single LSTM-based model simulates streamflow better than state-of-the-art basin-optimized hydrology models.

Benchmarking - ungauged



In [Kratzert et al. \(2019b\)](#) we took a similar approach, but trained only on a subset of basins, and evaluated on a hold-out basin set (simulating the *ungauged* setting). We performed 10-fold cross-validation, so that each basin is exactly once in the hold-out test set. Compared to basin-optimized (*gauged!*) SAC-SMA and the US National-Water-Model, the *ungauged* LSTM (purple) outperformed in average both hydrology models, even the gauged SAC-SMA.

Outlook

Future work

- Create a global dataset, consisting time series + catchment attributes (same data sources globally)
- Test if generalization is equally good if the model is transferred across countries/continents

[Google's Flood Forecasting Project](#): Google's effort for providing timely flood warnings for people in developing countries. Pilot project in India.

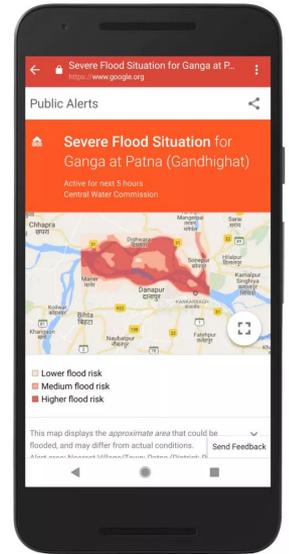


Image Source: Google