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Hybrid physics-AI-model applied to estuarine hydrodynamics

Introduction

Experience with the operational 2D tide and storm-surge model indicates that there are systematic biases in the Ems-Dollard estuary. The peak of the highest storm tides is under-estimated and the tidal amplitude is often under-estimated in the days following a storm. Here, we aim to improve the model accuracy by including an AI component coupled to the numerical model. The aim is to train the correction with available measurements.

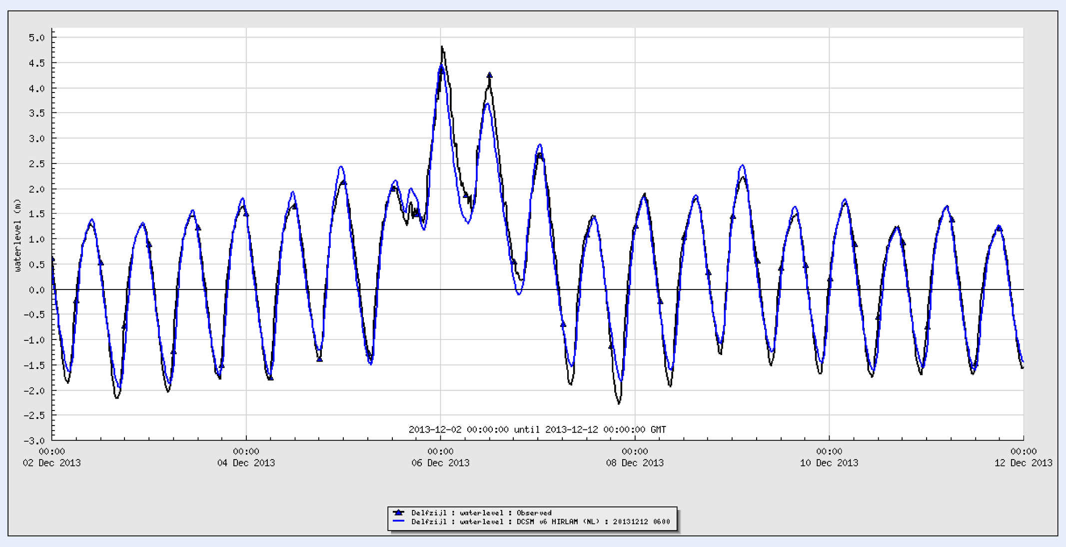
Figure 1: measurements and operational model at Delfzijl December 2013

Results

The simplified 1D model is less accurate than the operational model but preserves the main characteristics. Next, assimilation of 9 tide-gauges recovers most of the systematic biases (See Figs 1 and 2). A reanalysis was computed for October 2010 to 2014. Oct 2010 – Oct 2013 was used for training and the 4th year for validation. The LSTM network has 200 inputs and outputs, linked to the 200 state variables of the simplified model. It has 3 layers and an internal dimension 100. Figure 3 and Table 1 show the accuracy of the hybrid model for the validation period. The under-estimation of the storm peaks is recovered much better dan the increase in tidal amplitude after the storm.

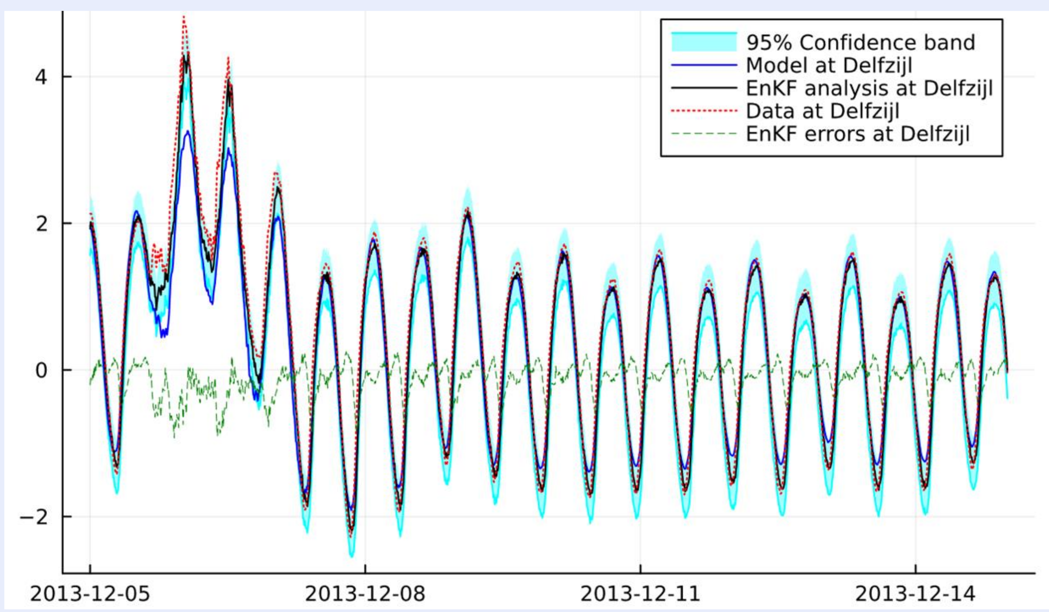

Figure 2: Simplified linear model and EnKF

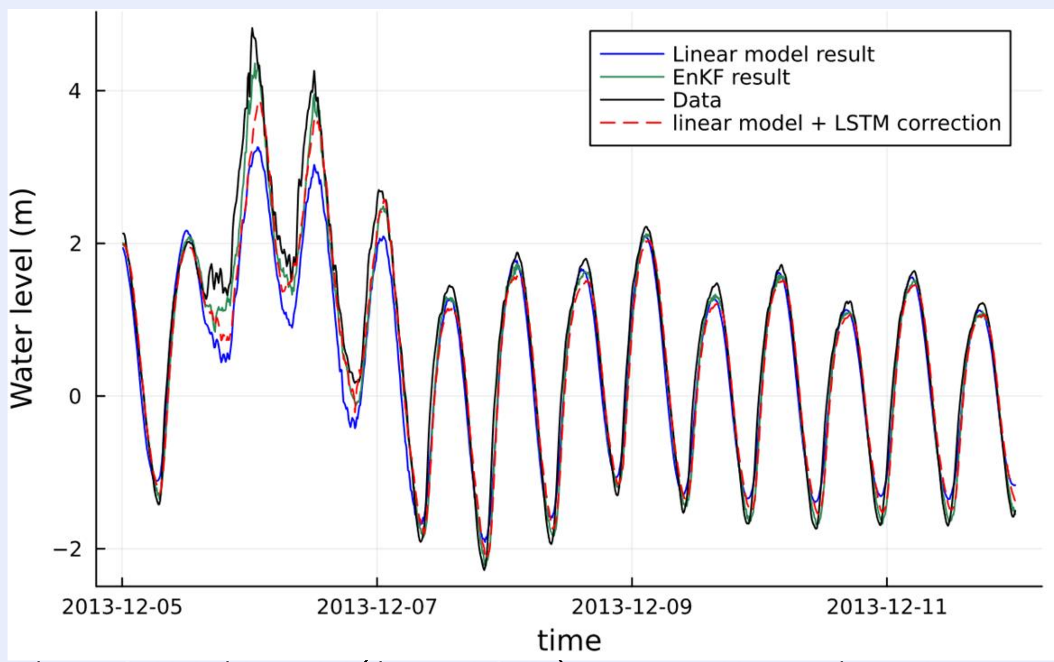

Figure 3: Hybrid model (linear+LSTM) compared to previous steps

Time period	Model RMSE (m)	EnKF RMSE (m)	Correction LSTM RMSE (m)	% change in RMSE (EnKF vs Model)	% change in RMSE (LSTM vs Model)
1 Oct 2013 – 1 Oct 2014	0.211	0.188	0.206	-9.672	-2.243
5 Dec 2013 – 12 Dec 2013	0.362	0.235	0.257	-35.159	-28.881

Table 1: Error statistics for simplified model, EnKF and hybrid model

Approach

Our approach is based on the idea by Brajard et al 2020, to train the network on states that are estimated using data-assimilation, i.e. using a reanalysis of the hydrodynamics.

Step 1: simplified model

First, we implemented a simplified 1D model to allow for more experimenting.

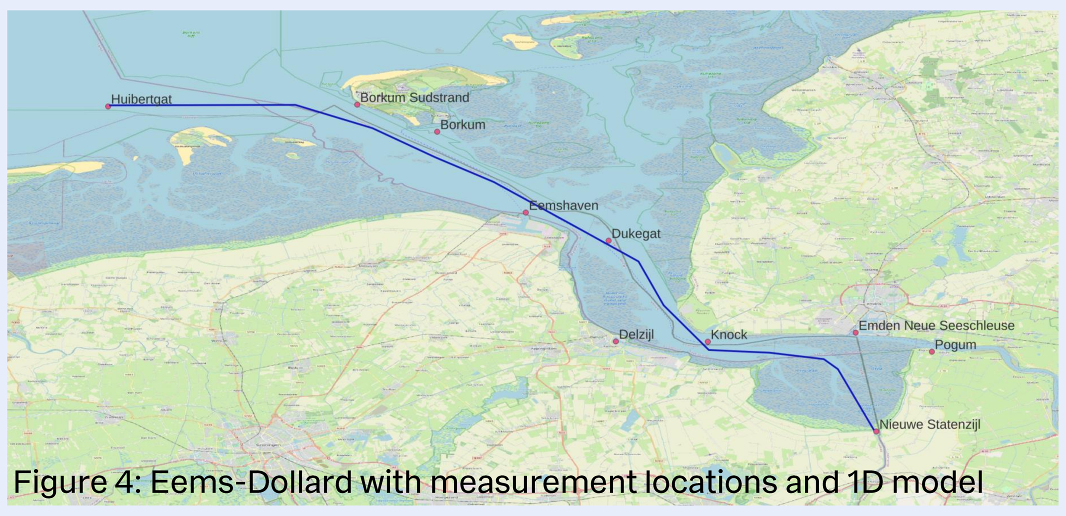
Figure 4: Eems-Dollard with measurement locations and 1D model

Step 2: EnKF

Next, we introduced system noise in the momentum equation and used the available tide gauge measurements to compute an accurate reconstruction of the state. An EnKF is applied to perform the data-assimilation.

Step 3: train network

Using the reconstructed states an LSTM AI model was trained that represents a correction within the model. We selected an LSTM architecture, since this has an internal memory or state, which is needed to detect the period following a storm. Many options exist. We first tested a correction to the output of the model for simplicity.

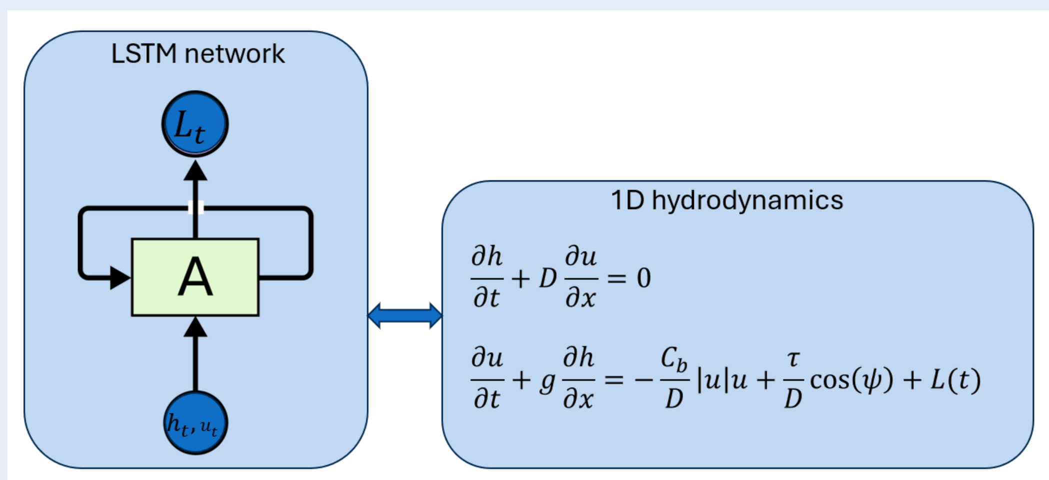

Figure 5: schematic diagram of hybrid AI/LSTM - hydrodynamic model

Step 4: test hybrid model

Finally, the AI and hydrodynamic models were coupled and tested for an independent period. Note that this approach allows for improved forecasting at any point in the model domain.

Conclusions

A hybrid machine learning and numerical modelling approach is applied to reduce systematic biases of the sea-level forecasts in the Eems-Dollard estuary in the Netherlands. The combined data-assimilation and training of an AI model can reduce these biases in part. The combined model is computationally efficient and provides updated estimates for all model variables, not just at the measurement locations.

Using a simplified 1D model we were able to quickly test several variants, but many others are possible. For example, the system error in the model can also be included as a modification of the friction and wind-stress terms. In future work, we aim to test several other variants and apply the approach to a larger 2D numerical model. If the estimates are formulated in terms of parameters shared by the 1D and 2D models, then one can try to apply the 1D estimates to the 2D model.

References

Brajard, J., Carrassi, A., Bocquet, M., & Bertino, L. (2020). Combining data assimilation and machine learning to emulate a dynamical model from sparse and noisy observations: A case study with the Lorenz 96 model. Journal of computational science, 44, 101171.

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