UNIVERSITY of VIRGINIA
SCHOOL of ENGINEERING & APPLIED SCIENCE
LINK LAB

Toward Forecasting Groundwater Table in Flood Prone Coastal Cities Using Long Short-term Memory and Recurrent Neural Networks

H21J-1776

AGU 100 FALL MEETING Washington, D.C. | 10–14 Dec 2018

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I. Background

- Coastal cities are facing recurrent flooding from relative sea level rise and more frequent extreme storm events
- During storms, the groundwater table can quickly rise toward the land surface
- High groundwater table level decreases storage capacity and increases runoff, stormwater system load, and flooding
- Data-driven modeling appropriate for forecasting urban groundwater table

Two neural networks were used to model groundwater table in Norfolk, VA, using historical and forecast data. Neural network performance with two training data sets is statistically evaluated with bootstrapping and t-tests.

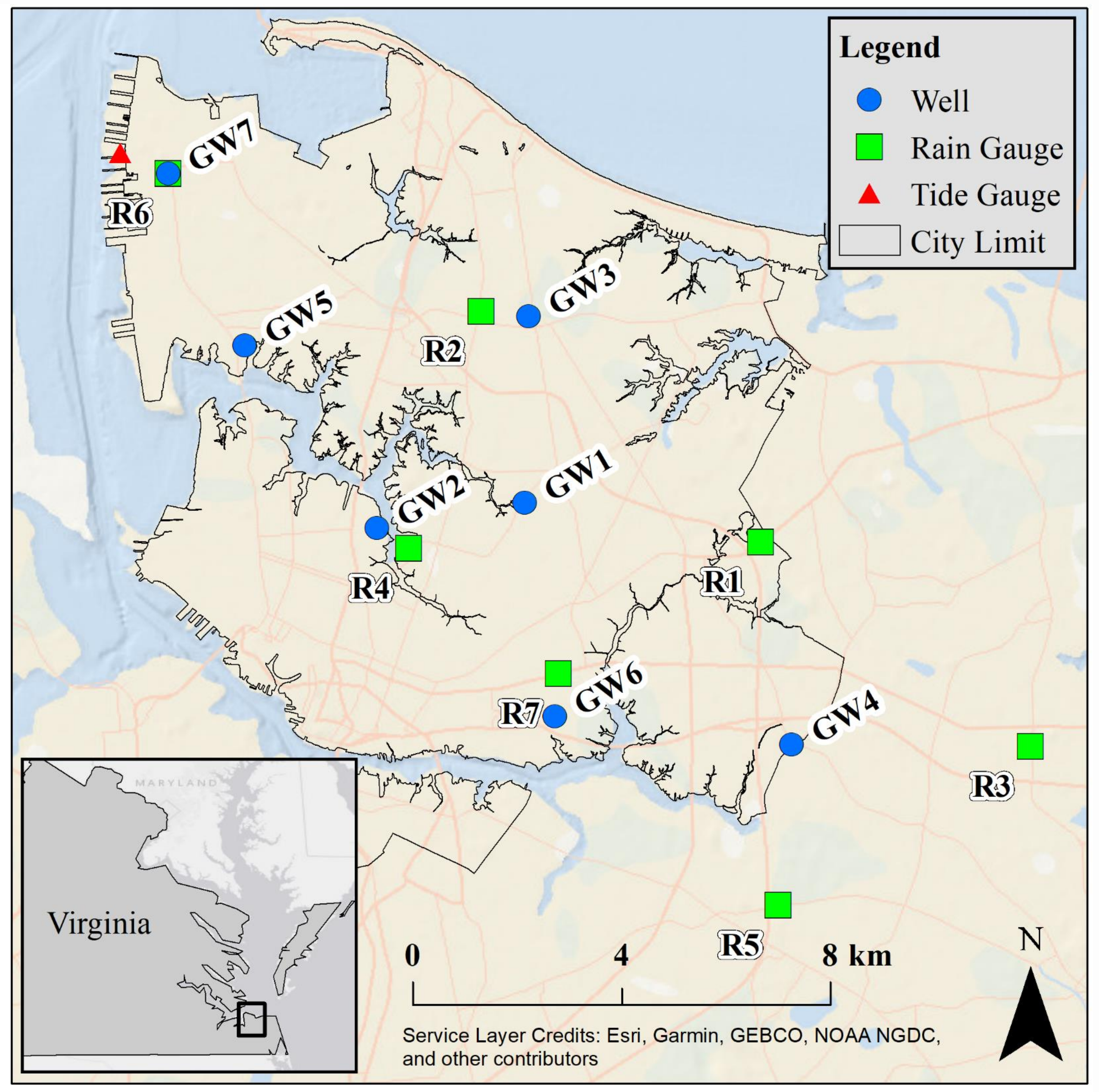

Figure 1. Gauge locations in Norfolk, Virginia.

II. Data and Methods

Preprocess: Hourly groundwater table, tide, and rainfall data from 2010-2018. Appropriate groundwater table response lags found with cross correlation analysis.

Two forms of training data:

- **Full** data set – cleaned continuous time series
- **Storm** data set – only time periods where groundwater table response to storm events was identified

Data sets were bootstrapped for model evaluations:

- Circular Block Bootstrapping
- 1000 replicates of each data set

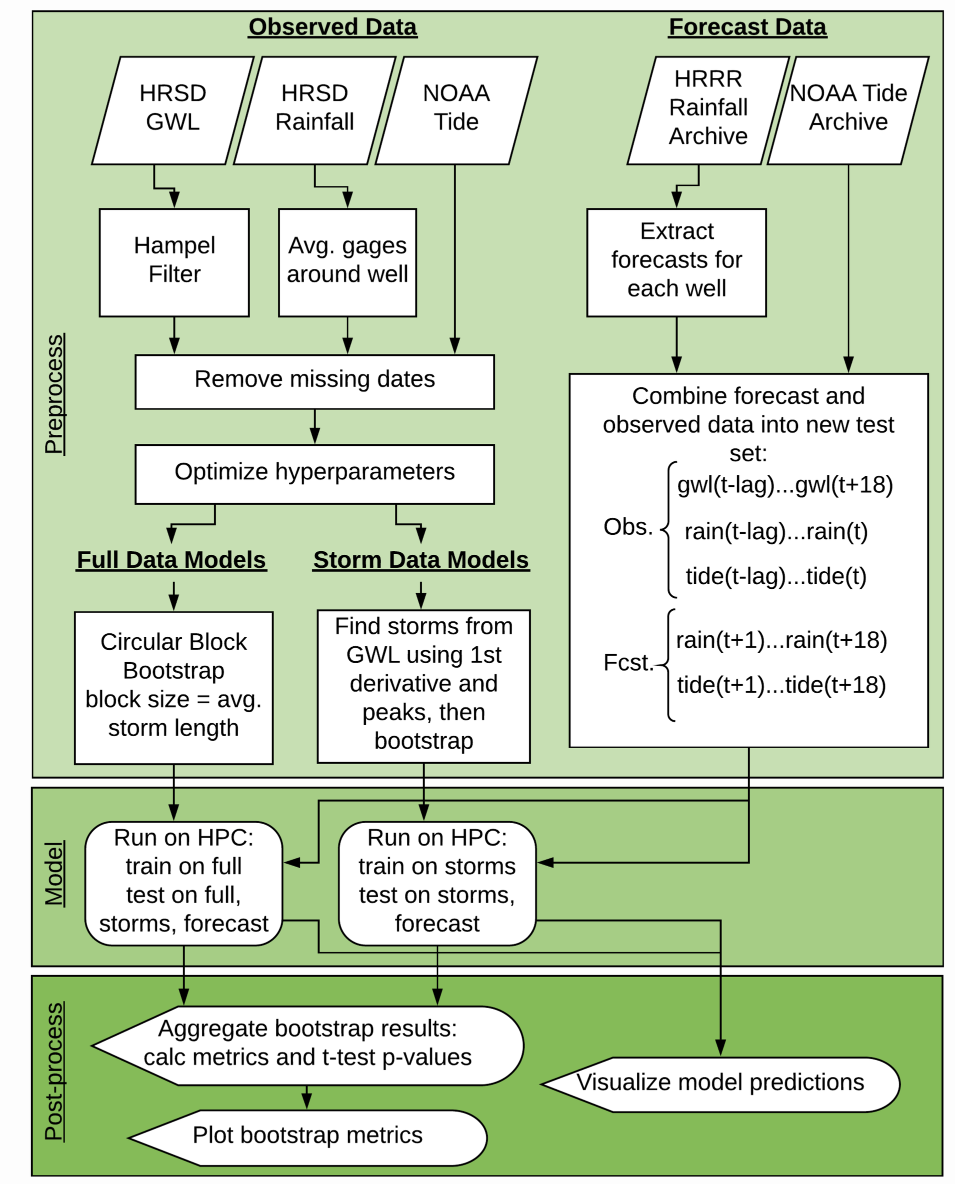

Figure 2. Study workflow.

Model: Recurrent (**RNN**) and Long Short-Term Memory (**LSTM**) neural networks were created using the Keras and **Tensorflow** Python libraries. The models were trained on each of the 1000 bootstrap data sets of the "full" and "storm" data sets to minimize the RMSE. Training was carried out in a HPC environment with a GPU.

Postprocess: After training, a number of test sets were presented to each model. A **t-test** was used to **evaluate** the significance of the differences in the mean RMSE between **model types and training data sets**.

III. Results

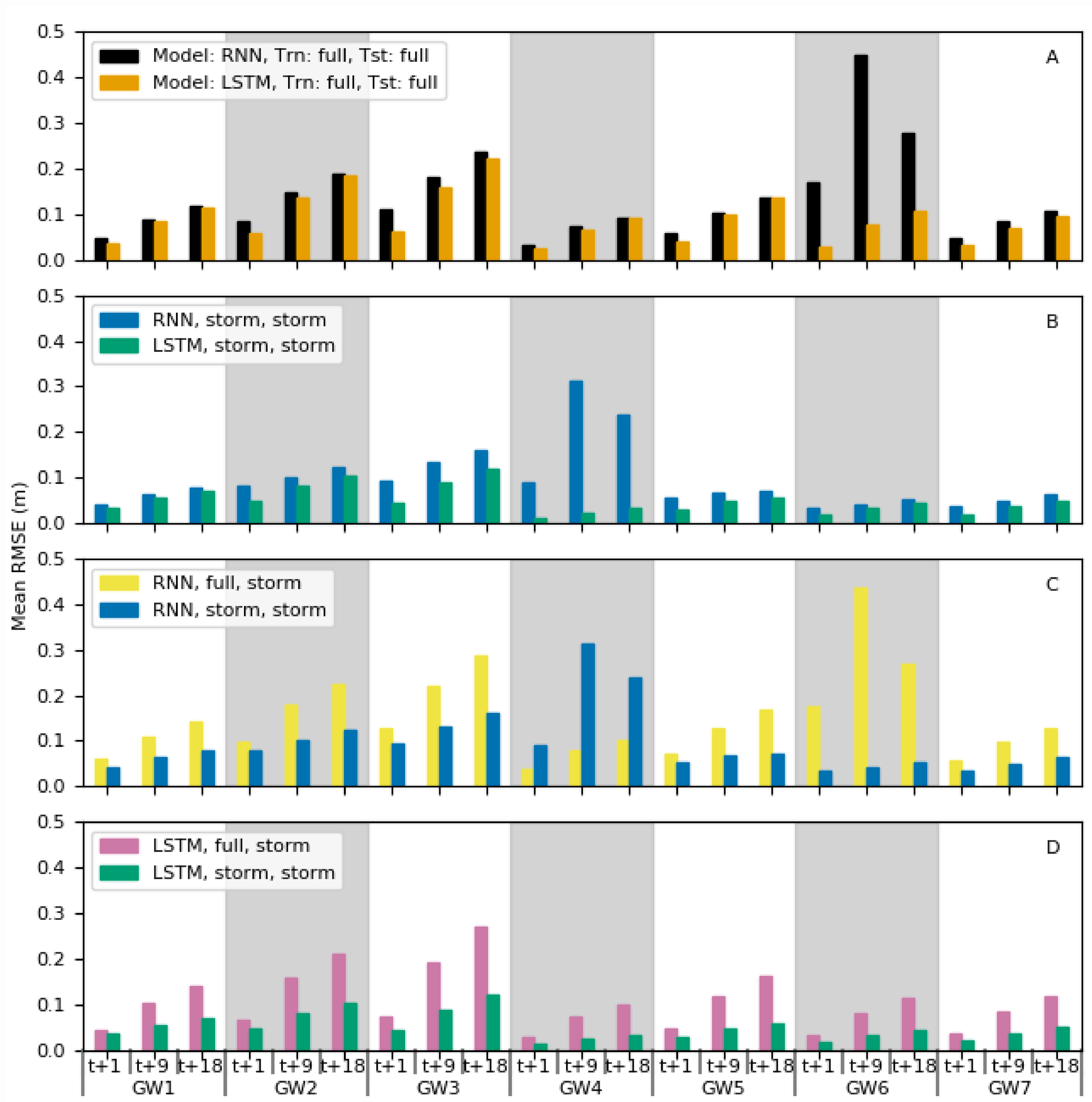

Figure 3. Mean RMSE values for model type/training data set at each well/forecast period. All comparisons significant with $p < 0.001$.

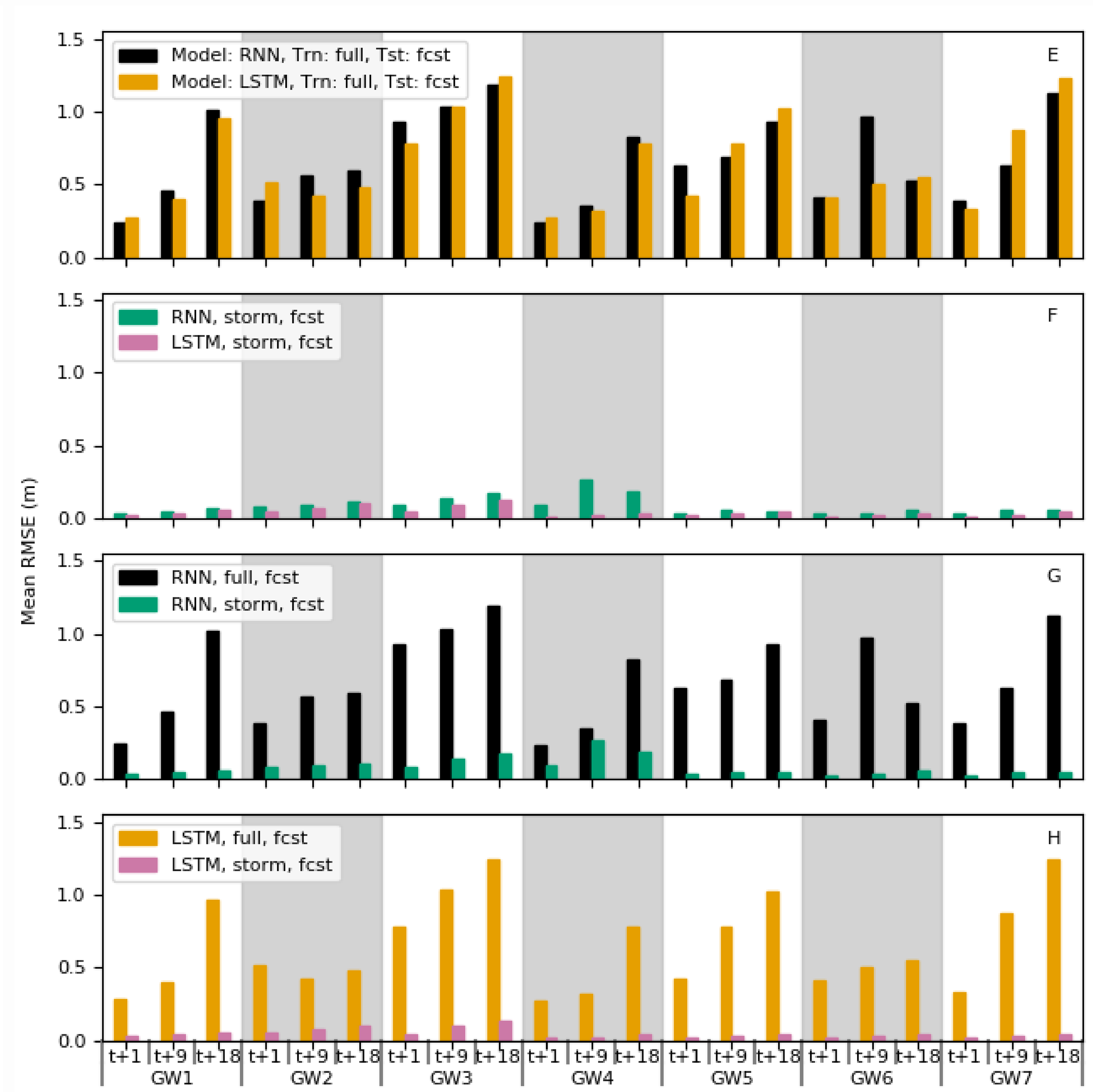

Figure 4. Mean RMSE values for model type/training data set at each well/forecast period when tested on forecast input data. All comparisons significant with $p < 0.001$ (except GW3 t+9 and GW6 t+1)

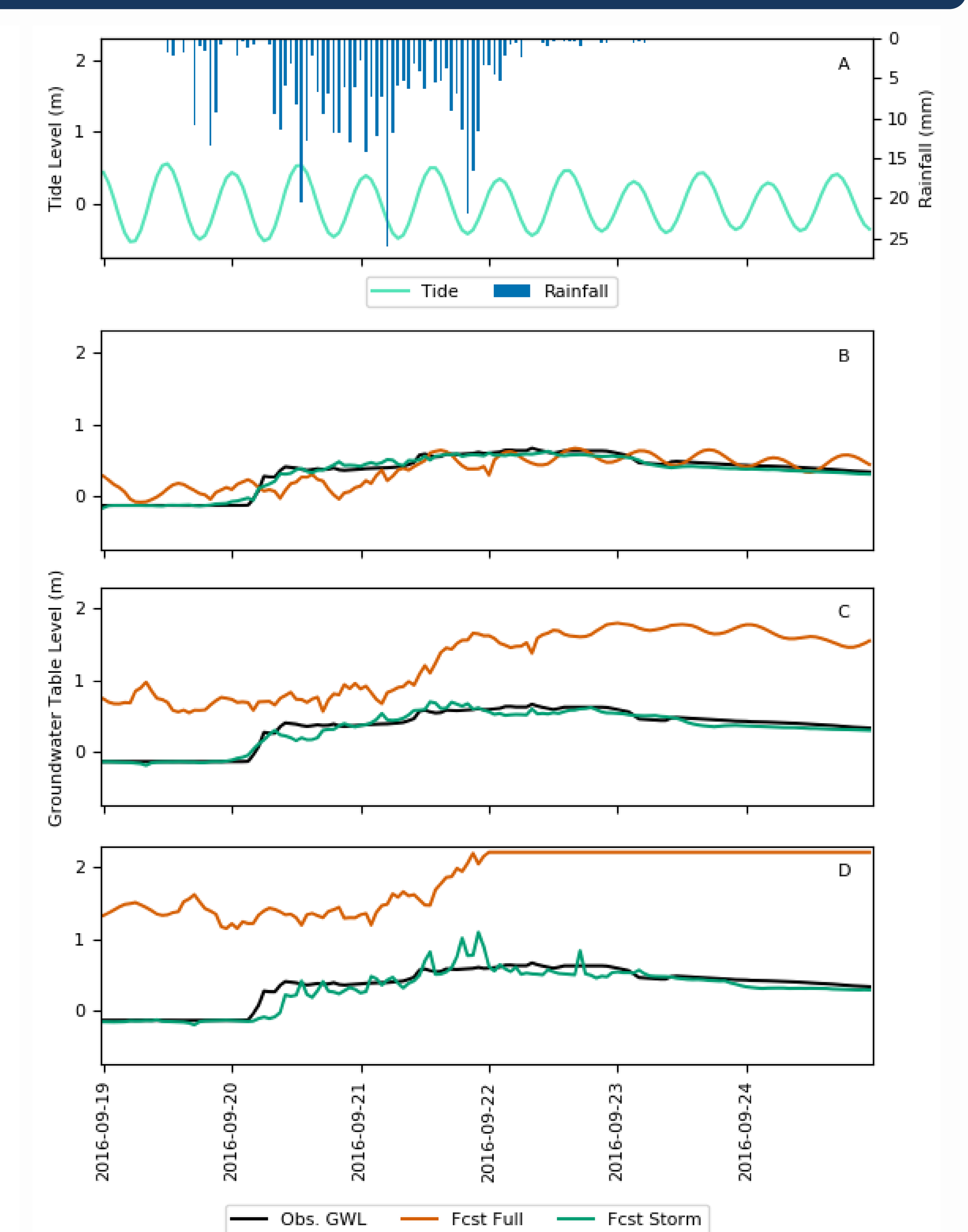

Figure 5. Groundwater table forecasts at GW1 from LSTM models trained with full and storm training sets. The t+1 (B), t+9 (C), and t+18 (D) forecasts are shown with the observed level.

IV. Conclusions

- This study fills a gap by creating hourly groundwater table predictions using both observed and forecast data in a "real-time" scenario
- LSTM networks have a slight but significant performance advantage over the vanilla RNN
- Models trained with storm data have a significantly lower RMSE than models trained with the full data set, especially when tested on forecast data
- Performance difference may relate to the number of dry/wet days in the full and storm data sets

Future work: Groundwater table forecasts could be incorporated into a 2D hydrodynamic model for increased flood prediction accuracy.

Acknowledgements

This work has been supported as part of a National Science Foundation grant: Award #1735587 (CRISP – Critical, Resilient Infrastructure Systems)

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