A Deep Learning Baseline for Spatiotemporal Precipitation Predictions

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Background

Weather forecasting utilizing numerical methods is computationally expensive due to the billions of degrees of freedom. Researchers seek to reduce computation cost by supplanting numerical weather models, at least in part, through deep learning models. This effort is hindered due to the difficulty in comparing deep learning models that are trained and optimized on different datasets. In this project, we develop a baseline toward a benchmark to facilitate comparisons among deep learning architectures.

Benchmark Dataset

- Precipitation rates in 5-minute intervals within a 1024×1024 km^2 region of the U.S. from 2001-2011.
- For each time frame, the dataset splits the region into 256 64×64 km^2 tiles to create more samples.

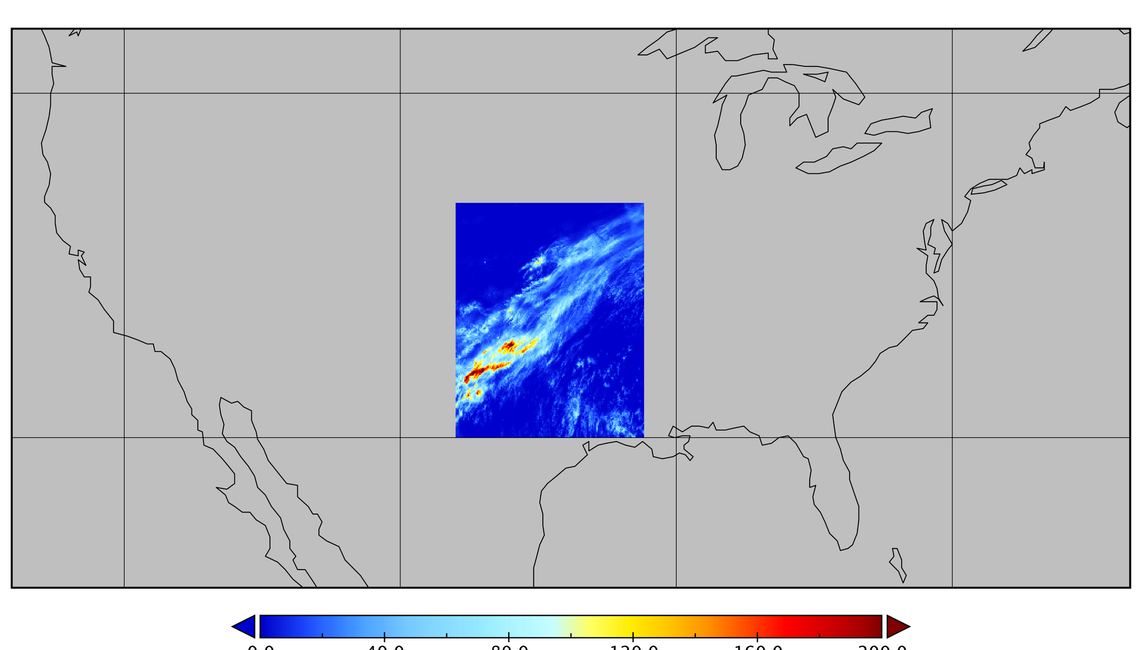

Figure 1: Region covered by benchmark dataset

References

[1] J. Zhang, J. Gourley. Multi-Radar Multi-Sensor Precipitation Reanalysis (Version 1.0) (2018).
[2] X Shi, et. al. Convolutional LSTM Network: A Machine Learning Approach for Precipitation Nowcasting (2015).

Baseline Results

We trained the convLSTM baseline model using 4 years of unbalanced training data (2001-2004) over a 64×64 km^2 tile. We then compared the the model's predicted precipitation to the observed precipitation over a 24 hour period for different amounts of precipitation:

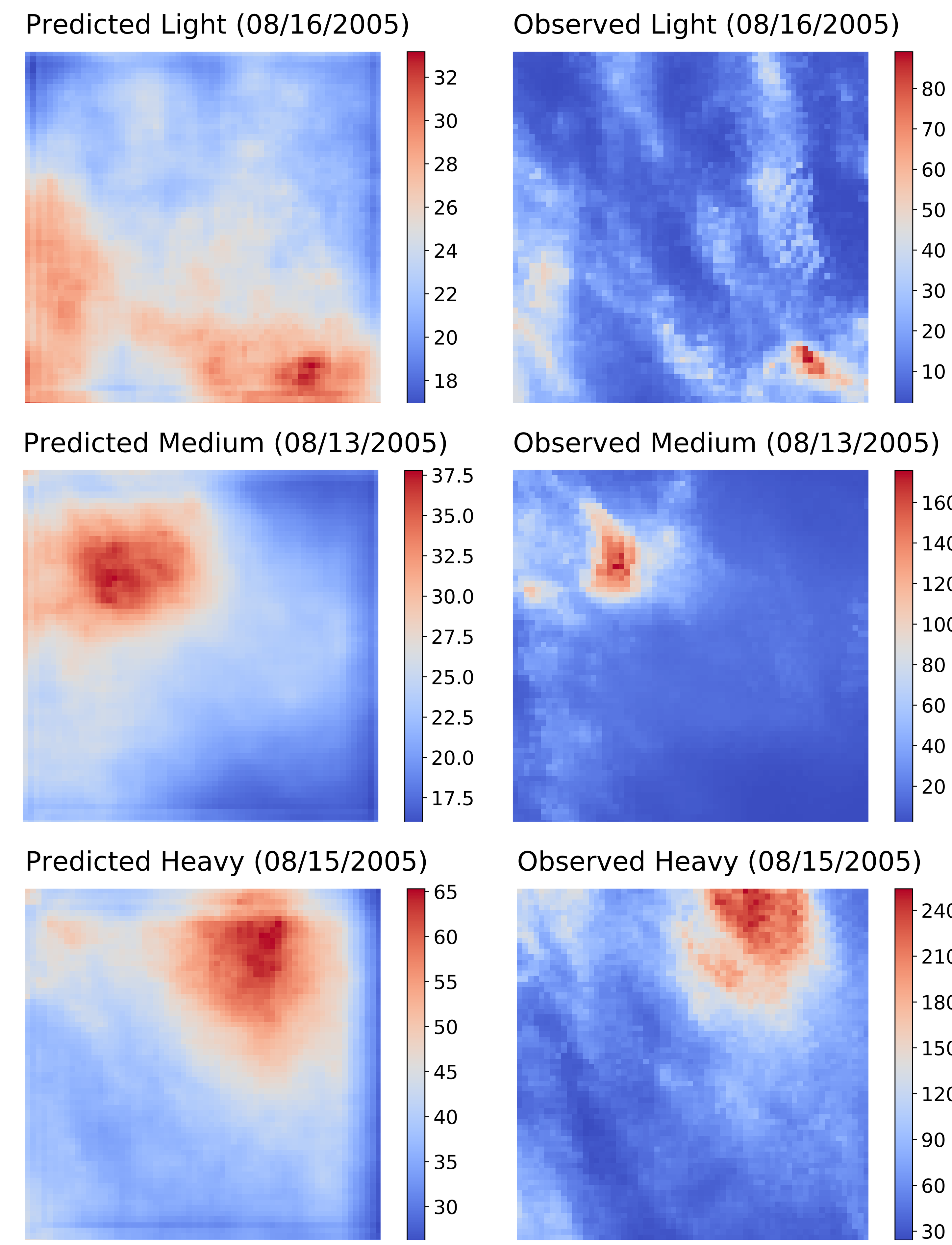

Figure 2: Comparison of predicted and observed precipitation rates (mm/day) for varying amounts of rainfall. Note different color scales.

- Predictions capture general spatial patterns.
- Model often underpredicts observed precipitation rates.

Baseline Model Architecture

We use a convolutional long short-term memory (convLSTM) model, which are designed for spatiotemporal data as they are capable of learning long-term dependencies with respect to location.

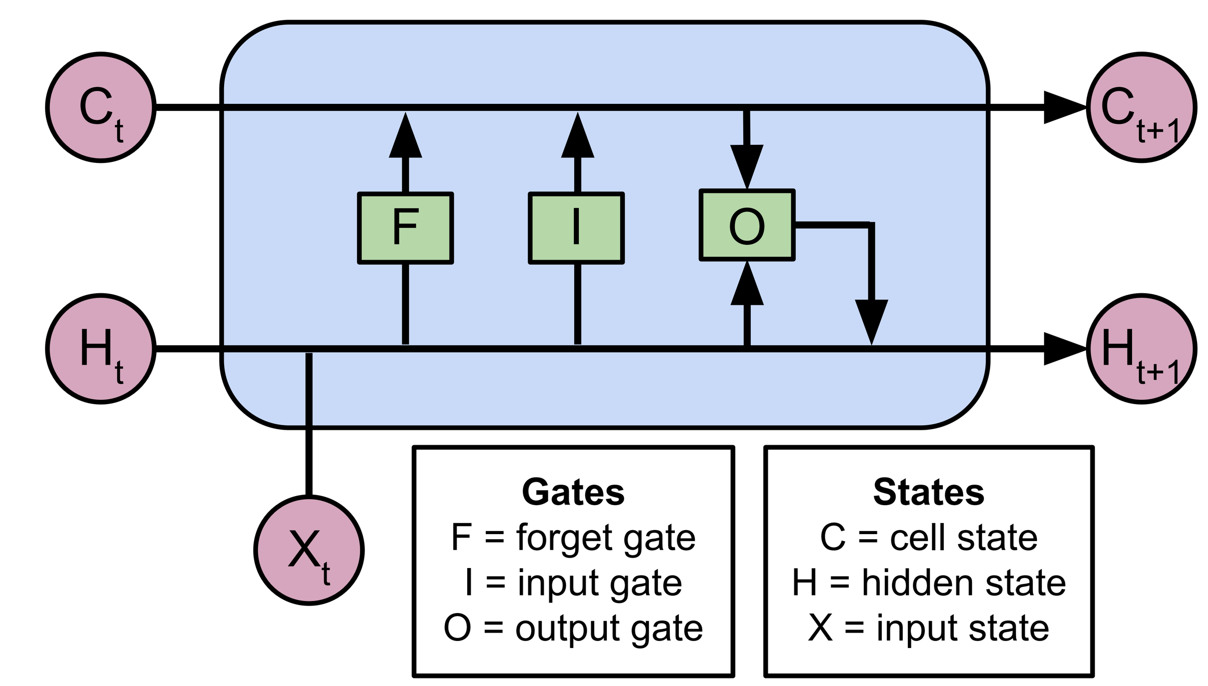

Figure 3: convLSTM block

- convLSTM design consists of recursive blocks.
- C, H, X are input and output data for each block
- C carries important information between blocks.
- F, I, and O gates take input data and control what information goes in and out of C.

Conclusions

- Defined benchmark dataset for precipitation rates.
- Implemented baseline model convLSTM that utilizes benchmark data.
- Baseline model showed promise toward skill in spatiotemporal precipitation prediction.

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