NOAA ROSES Semi-Annual Report

Reporting Period: March 2021 – August 2021 (2nd report)

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Project Title: Assimilating GOES-R Latent Heating in FV3 using Machine Learning

Executive Summary (1 paragraph max)

The main objective of this project is to use the high-resolution information from GOES-R Advanced Baseline Imager (ABI) and Geostationary Lightning Mapper (GLM) to improve short-term forecasts of high-impact weather hazards. This will be accomplished through using machine learning (ML) to derive three-dimensional fields of latent heating to spin-up convection in the Rapid Refresh Forecast System. The secondary goal of this project is to provide new data assimilation capabilities for the new generation of FV3 dynamical core models at NOAA, utilizing the Joint Effort for Data Assimilation Integration (JEDI) framework.

Progress toward FY20 Milestones and Relevant Findings (with any Figs)

- Provided GREMLIN 3D synthetic radar reflectivity fields for a retrospective simulation running September 4-10, 2020. After some analysis, Amanda Back concluded that the storms during that period were too strongly forced: the models didn't have many misses and the impacts of radar and lightning assimilation experiments were difficult to parse. They started investigating a May 14-19, 2021, period, finding more interesting cases. They also made changes to the latent heating methodology – applying two 15-minute periods at the top of each hour, rather than the full hour of latent heating adjustment, which allows the model more time to run in forecast mode and adjust to the latent heating forcing. Initial indications are that this cycled heating adjustment is very beneficial.

- Made progress on improving and extending GREMLIN model capabilities using multi-task learning and advanced loss functions:
  - Successfully implemented a multi-task learning framework for convective / stratiform classification, which is a required input to Yoonjin's vertical profile model.
  - Added GLM Lightning Area to GREMLIN. **Figure 1** Panels (D) and (E) compare GREMLIN without and with lightning area and show that including lightning area reduces over-prediction of stratiform coverage (east central Iowa) and increases convective intensity (south-eastern Iowa). GREMLIN has learned that smaller lightning areas imply stronger echoes that are associated with convective cores and that large lightning areas are associated with stratiform areas and reduced reflectivity (**Figure 2**).
  - Added uncertainty estimates at each pixel using Barnes log-likelihood loss function.

- Prepared the CONUS4 dataset, which extends GREMLIN to run on the portion of the Full Disk domain with GLM coverage.

- Yoonjin Lee revised her manuscript on the vertical profile model for latent heating.

- Publications:
  - Ebert-Uphoff, I., R. Lagerquist, K. Hilburn, Y. Lee, K. Haynes, J. Stock, C. Kumler, and J. Q. Stewart, 2022: CIRA Guide to Custom Loss Functions for Neural Networks in Environmental Sciences – Version 1. arXiv:2106.09757.

- Presentations:
  - Hilburn, K., 2021: GOES Radar Estimation via Machine Learning to Inform NWP (GREMLIN), *STAR-CIRA Mini Symposium*, 9-March.
  - Hilburn, K., 2021: GOES Radar Estimation via Machine Learning to Inform NWP (GREMLIN) – And Aviation Nowcasting? *Presentation to the Aviation Weather Center*, 8-June.

Plans for Next Reporting Period

- Preparing manuscript for AMS *AIES* journal (NOAA AI Workshop Special Collection) analyzing the temporal consistency of GREMLIN predictions.

- Further improvements to GREMLIN:
  - Our experiments with a deeper model during the current period found the model stops learning after five layers depth. David Hall (NVIDIA) strongly recommends using a "ResNet" approach, which we will test along with "dilated convolutions", to get a larger receptive field for capturing synoptic scale precipitation patterns.
  - Larger dataset training: The CONUS4 dataset is too big to train on one GPU or to load all the data in memory. This requires use of a custom data generator, and we are in contact with David Hall (NVIDIA) to deal with the tricky implementation issues.
  - Using Libby Barnes latest loss function, which accounts for non-Gaussian behavior.

- Yoonjin Lee is attending the JEDI Academy October 4-8.

- Presentations scheduled during the next reporting period:
  - Hilburn, K., 2021: Machine Learning in Atmospheric Science, *CIRA Jamboree*, 9-Sep.
  - Hilburn, K., Y. Lee, and I. Ebert-Uphoff, 2021: Improving GREMLIN: A Case Study in AI Application Development, *3rd NOAA Workshop on Leveraging AI in Environmental Sciences*, 15-Sep.
  - Lee, Y., K. Hilburn, and I. Ebert-Uphoff, 2021: Exploring Ways to Effectively Use Temporal Satellite Images in Detecting Convection from GOES-16, *3rd NOAA Workshop on Leveraging AI in Environmental Sciences*, 14-Sep.
  - Hilburn, K., Y. Lee, and I. Ebert-Uphoff, 2021: GREMLIN: GOES Radar Estimation via Machine Learning to Inform NWP. *Fall AGU Meeting*, A047.
  - Lee, Y., C. D. Kummerow, and I. Ebert-Uphoff, 2021: Applying Machine Learning Methods to Detect Convection Using GOES-16 ABI Data. *Fall AGU Meeting*, A086.
  - Ebert-Uphoff, I., R. Lagerquist, K. Hilburn, Y. Lee, K. Haynes, J. Stock, C. Kumler, and J. Q. Stewart, 2022: How to Develop Custom Loss Functions for Neural Networks in Meteorology. *AMS Annual*, 21AI.
  - Back, A., A. Kliewer, J. R. Mecikalski, K. Hilburn, Y. Lee, E. Sebok, D. Dowell, E. C. Bruning, M. Xue, R. Kong, S. Benjamin, E. P. James, C. R. Alexander, G. Ge, K. Pederson, and S. Weygandt, 2022: Novel Convection-Indicating Satellite Products Assimilated in Experimental Rapid Refresh Systems, *AMS Annual*, 26IOAS.

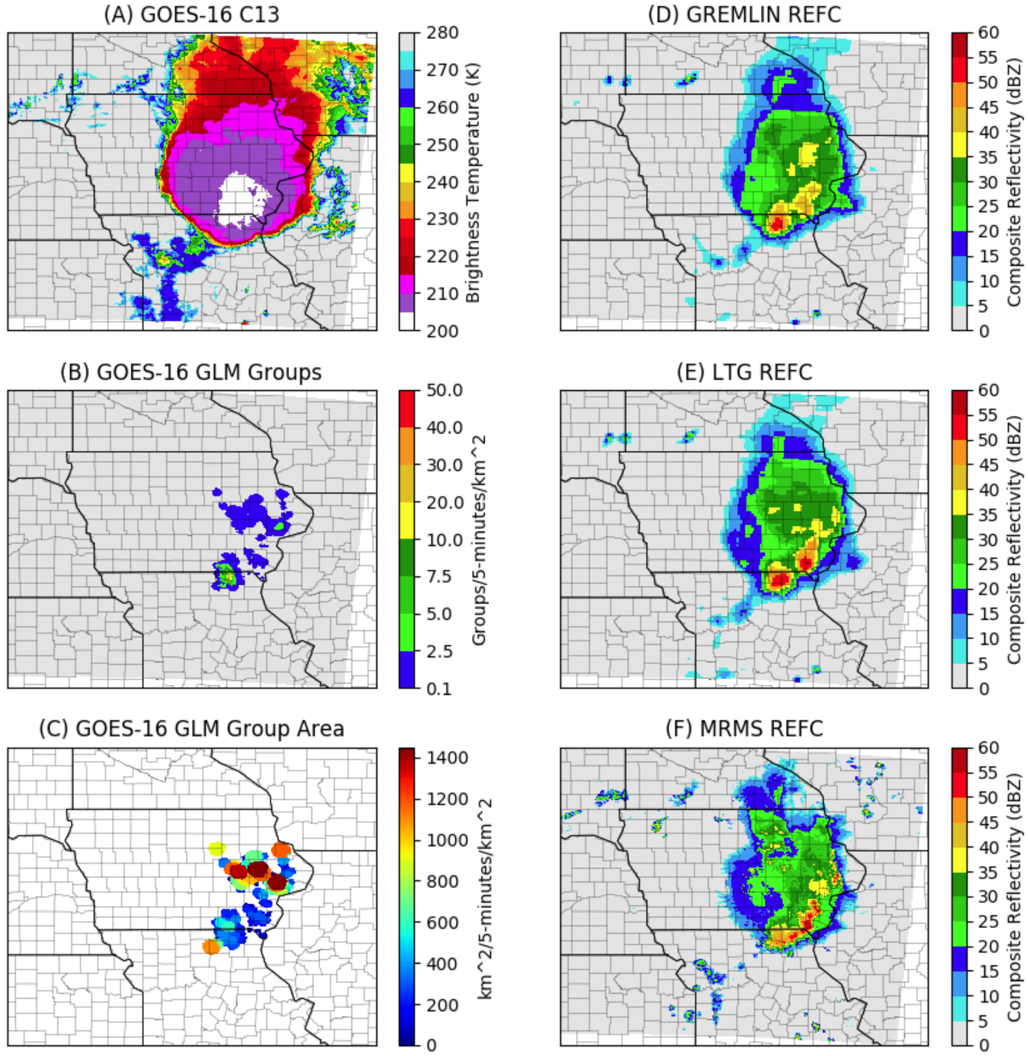

Figure 1. Example from 2019-07-17 19:45Z showing (A) GOES ABI, (B) GOES GLM Group Extent Density, (C) GOES GLM Average Group Area, (D) GREMLIN V1 composite reflectivity, (E) GREMLIN Experimental Version with Lightning Area, and (F) MRMS composite reflectivity.

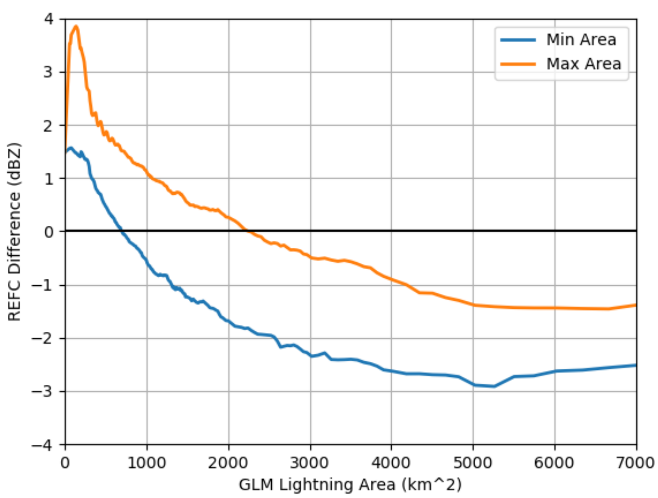

Figure 2. The average composite reflectivity difference between GREMLIN with lightning area minus GREMLIN without lightning area, computed over April-July 2020.