NOAA ROSES Semi-Annual Report

Reporting Period: September 2021 – February 2022 (3rd report)

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Project Title: Enhancing forecast applications of the GOES-R GLM in tropical cyclones using multi-platform data fusion and AI to assess environment and storm structure

Executive Summary (1 paragraph max)

This project aims to utilize machine learning (ML) to aid in the development of an automated real-time predictive tool that can assess links between the Geostationary Lightning Mapper (GLM), tropical cyclone (TC) structure, and TC intensity change to improve intensity forecasts. The Year 1 milestones focus on data collection and data processing in anticipation for the machine-learning training and tool development in Years 2 and 3. Steady progress continued during this reporting period, with the main accomplishments focused on wrapping up the basin-wide climatology, continued assembly and expansion of the ML dataset, and ML model development aiming towards TC intensity prediction. The core project team continues to hold bi-weekly meetings to maintain communication and keep the project on track.

Progress toward FY21 Milestones and Relevant Findings (with any Figs)

Significant progress was made on the climatology of lightning in the Atlantic and Pacific Oceans and how it relates to other environmental measurements. GLM was more likely to observe lightning in convection over warmer sea surface temperatures (SSTs), larger ocean heat content (OHC) values, and closer to land (Figure 1). The aerosol optical depth (AOD) for various particles (dust, sulfates, salts, and smoke) was also analyzed. AOD was higher for most lightning-producing convection over the ocean, though there were mixed signals with dust, likely due to the added complexity of dry air with Saharan Air Layer outbreaks.

The climatology work also analyzed diurnal variability and correlations between lightning and the aforementioned environmental variables in five different regions prone to tropical cyclone activity. While warmer oceans were found to be beneficial for the formation of lightning-producing deep convection, there appeared to be no correlation between SST/OHC and the rate of lightning groups observed by GLM. The ground-based WWLLN was also compared to GLM in the selected TC-prone regions to determine the impact of GLM data quality issues, such as the false “Bahamas bar” lightning, and diurnal detection variability on the results of the climatology. There were some differences noted between in the diurnal peak between the two sources. Regions like the Atlantic main development region observed deep convection with lightning during peak hurricane season only ~2.5% of the time, whereas regions like the Gulf of Mexico observed lightning ~15% of the time. Knowing these correlations to environmental, temporal, and spatial factors gives us a better framework for designing our ML model, since it gives us a better idea of the scenarios when lightning may be favorable or unfavorable.

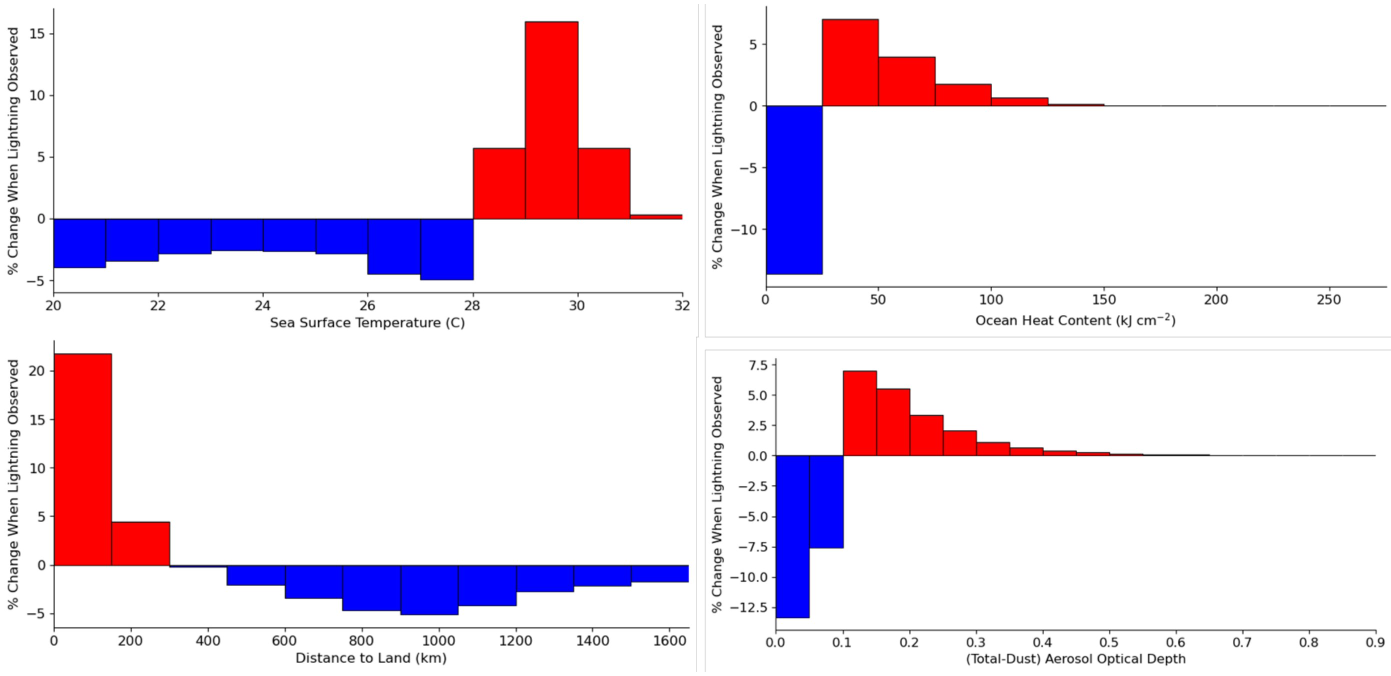

Figure 1. *The percent change in the probability distribution of (top left) sea surface temperature, (top right) ocean heat content, (bottom left) distance to land, and (bottom right) aerosol optical depth when lightning was observed compared to the overall distribution of oceanic convection.*

During this period, we also made several advances to complete the TC-centric dataset. We added quality-controlled ISS-LIS data for another point-of-comparison (we already have WWLLN). Additional lightning statistical moments were added, so that now we have minimum, mean, and maximum for both lightning group area and lightning group energy. These were found to add discriminating power during our exploration of ML-based GLM quality-control measures, and they also help with distinguishing lightning coming from convective versus stratiform pixels. We also updated (i.e., download, resample, and accumulate) all our datasets through 2021. Thus, the dataset now consists of the five-year period 2017-2021, which will allow us to perform cross-validation of ML models using a leave-one-out approach. This time-period provides 249 cases of rapid intensification (based on 30 kts in 24 hours) from 53 storms (Table 1). Software refactoring was performed to avoid running out of memory during dataset assembly and to resample GFS model fields more efficiently. At present, the dataset consists of 5,541 samples, which is up from 3,818 samples reported last period. Valid samples require both ABI and GLM data to be present, the storm box must be fully within the GLM event grid coverage and not be too far out on the limb (ABI pixel area < 40 km^2). Each sample consists of a 512 x 512 image for each variable on the 2-km ABI Full Disk grid, sampled at 0, 6, 12, and 18Z, including both GOES-16 and GOES-17. Duplicate samples, which happens with the ATCF dataset used to define storm tracks, are excluded; but when a storm has coverage from both G16 and G17, both are included so that we can compare the effects of viewing angle on lightning. The variables currently included in the dataset are given in Table 2.

Table 1. *List of storms with RI cases that have GOES data coverage.*

Year	Atlantic	East Pacific
2017	Franklin, Harvey, Irma, Jose, Katia, Lee, Maria, Nate	Dora, Eugene, Fernanda, Kenneth, Otis, Max
2018	Beryl, Florence, Michael	Aletta, Bud, Hector, John, Lane, Norman, Olivia, Rosa, Sergio, Willa
2019	Dorian, Jerry, Lorenzo	Barbara, Erick, Juliette, Kiko
2020	Laura, Teddy, Delta, Epsilon, Zeta, Eta, Iota	Douglas, Genevieve, Marie
2021	Elsa, Grace, Ida, Sam	Felicia, Hilda, Linda, Olaf, Rick

Table 2. *List of variables in the TC-centric dataset to be used for the ML model.*

Type	Number	Details
ABI	6	C07, C09, C13; TB and DQF
GLM	21	Group extent density, Min/Mean/Max Area/Energy; 1H, 3H, 6H accumulation
Storm geometry	3	Distance from center, azimuth from motion direction, azimuth from SHIPS shear vector
Satellite geometry	1	Zenith angle
Solar geometry	2	Zenith angle, Sun glint angle (specular)
Land	2	Mask, distance
Environmental	3	SST, OHC, AOD
GFS	12	U, V, T, RH, HGT at 200, 850 mb; USHRD, VSHRD
WWLLN	3	Flash extent density; 1H, 3H, 6H accumulation
ISS-LIS_QC	21	Group extent density, Min/Mean/Max Area/Energy; 1H, 3H, 6H accumulation
Intensity	2	Vmax, MSLP
Intensity change	≤24	Vmax for 6, 12, 18, 24, 30, 36, 42, 48, 54, 60, 66, 72 hours; actual and OFCL forecast
Storm metadata	9	Date/time, name, id, eye diameter, development level, basin, sub-region, motion speed and direction, center latitude/longitude
Satellite metadata	7	ABI bounding box, orbit slot, ABI yaw flag, ABI focal plane flag, GLM validation level, GLM build number, GLM update name

During this period, we also began work on development of the GLM TC RI prediction ML model. The architecture consists of a convolutional neural network on the front end to process the image inputs, and then has a dense neural network on the back end to output a scalar value of the predicted intensity change at different lead times. We explored 256 potential networks by varying the number of layers and filters in both the convolutional and dense components of the network. The goal is to construct a latent space which is not too large or too small. We then trained these models on the TC-centric dataset to predict V_{max} and 24-hour V_{max} change. We evaluated using just C13 versus C13 and GLM GED together, and linear versus logarithmic scaling of GLM. We found that 22% of the models failed to learn at all, and we excluded those from our analysis based on the condition that the coefficient of determination R^2 was negative for those models. Our results from the using GLM provided increased predictive value over just using ABI alone. We found that logarithmic scaling consistently produced better predictions than linear scaling. Plotting the root-mean-square-error RMSD and R^2 versus the number of parameters in each model, we found that errors decreased rapidly as the number of parameters increased beyond 10,000, but then leveled-out around 20,000 parameters, and that significant overfitting occurred for > 40,000 parameters. We will focus on this part of the hyperparameter space (around 20,000 parameters) as we continue to train and evaluate our ML RI model. This is around where ML RMSD values fall below the baseline values of 5 kts on V_{max} and 8 kts on 24-hour V_{max} change.

The project was included in presentations at the:

- American Geophysical Union (AGU) Fall Meeting – December 2021
  GLM Applications for Tropical Cyclone Analysis and Forecasting
- 102nd American Meteorological Society (AMS) Annual Meeting, 18th Annual Symposium on Operational Environmental Satellite Systems – January 2022
  Evaluation of lightning climatology in the Atlantic and Eastern Pacific using data from the Geostationary Lightning Mapper

Plans for Next Reporting Period

With the basin-wide climatology mostly complete, the team plans to evaluate a TC-centric look with the same datasets for pattern recognition and differences from the large-scale. Additionally, work will continue with various iterations of ML runs with the extensively packaged datasets, and we will continue to evaluate integrating less-frequently-available observations from aircraft and microwave satellite imagery to incorporate TC structure. The climatology results will be presented at the American Meteorological Society (AMS) 35th Conference on Hurricanes and Tropical Meteorology in May, and we are anticipate presenting more of the ML work at the AMS Madison Collective Meeting in August.