673 Correcting Errors in Mesoscale Convective System Quantitative Precipitation Forecasts of Intensity, Timing, and Location Using Machine Learning Algorithms

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Introduction

- Convection-allowing models have been shown to improve simulations of heavy rain with warm-season convection
  - They improve the skill in quantitative precipitation forecasts (QPF), but still struggle with precipitation intensity, timing, and location which negatively impacts flood forecasts
  - The goal of our research is to create a machine learning (ML) based post-processor for ensemble QPF that will predict likely errors to improve uncertainty estimates

Methods

- Method for Object-based Diagnostic Evaluation (MODE) was used to examine mesoscale convective system (MCS) QPF errors for 384 cases within the High-Resolution Ensemble Forecast members (HREF) during the months of May-October of 2018-2023 and several metrics provided by MODE are being used as predictors for the training of ML algorithms
- To include additional predictors for ML training, 22 atmospheric parameters were retrieved from the Storm Prediction Center mesoanalysis; Parameters were collected from a 5x5 grid centered on the centroids of the forecast objects
- ML algorithms currently being trained & very early results prior to feature selection & parameter tuning:
  - **Linear Regression**
    - N/S Displacement Prediction; *R^2: 0.377*
    - E/W Displacement Prediction: *R^2: 0.319*
    - RMSE: *[149.34734438509773, 125.27514623919052] (N/S, E/W) [in km]*
  - **Ridge Regression**
    - RMSE: *[136.8165712838063, 117.09144858634627] (N/S, E/W) [in km]*
  - **XGBoost**
    - RMSE: [139.55530801637607, 125.66827209547353] *(N/S, E/W) [in km]*
  - **Random Forest**
    - RMSE: [123.05427623331967, 117.43077514510055] *(N/S, E/W) [in km]*

Acknowledgements

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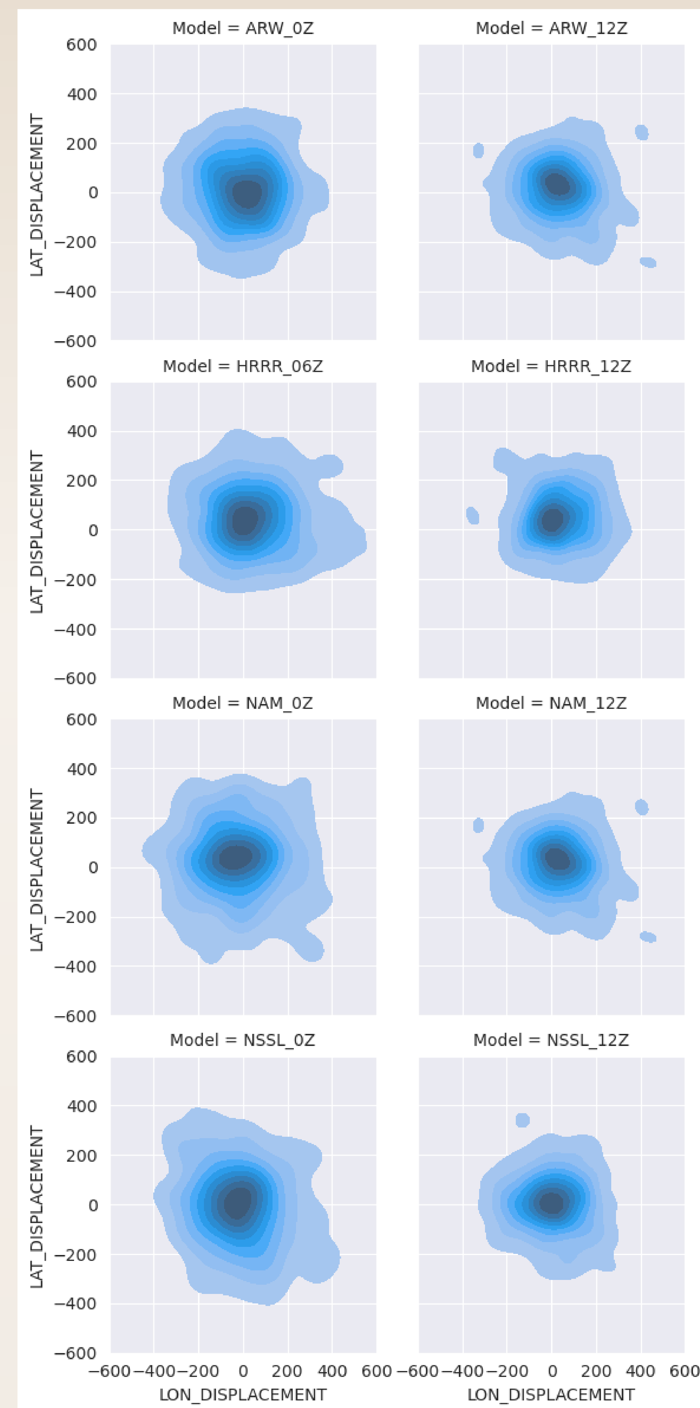
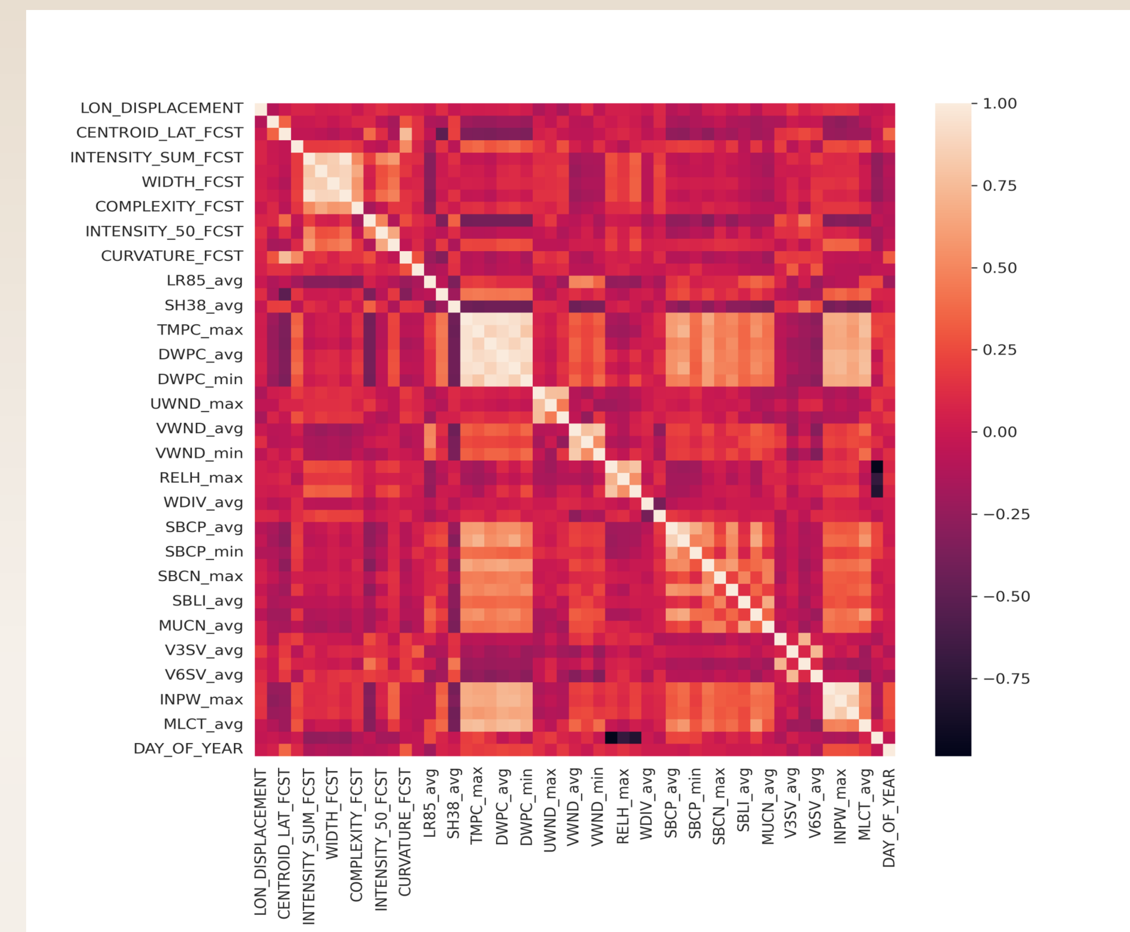
Data Analysis and MODE Output

Kernel Density Estimations of Displacements for Each Model



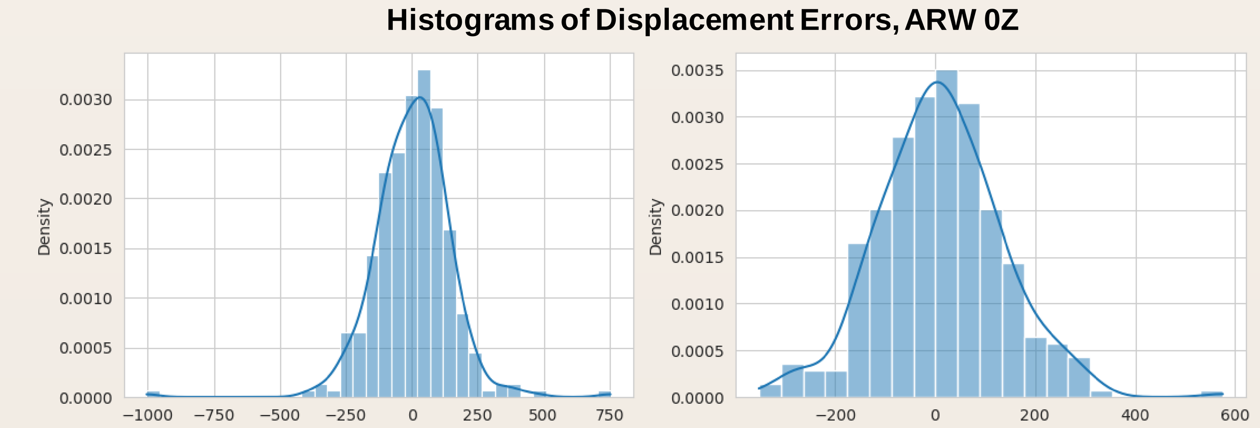
Darker shades represent a higher concentration of displacement errors (in km) with that value. Earlier model runs generally show a broader distribution of longitudinal displacement errors, with the HRRR 06Z being the only notable exception.

Correlation Heat Map Between Variables

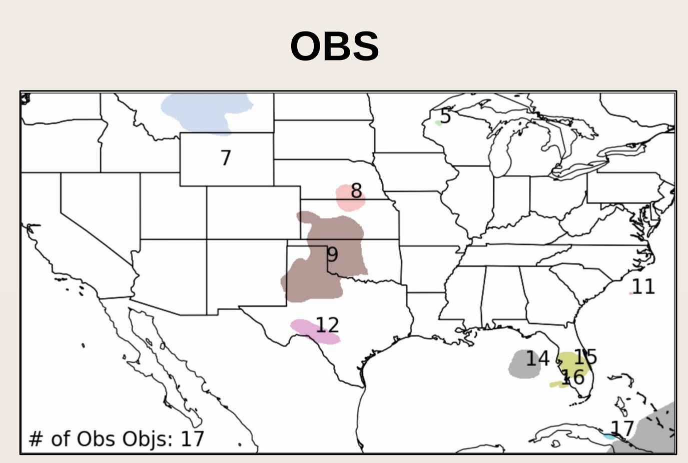


Plot illustrating correlation between the various predictors; Lighter colors represent positive correlation and vice-versa.

Histograms of Displacement Errors, ARW 0Z

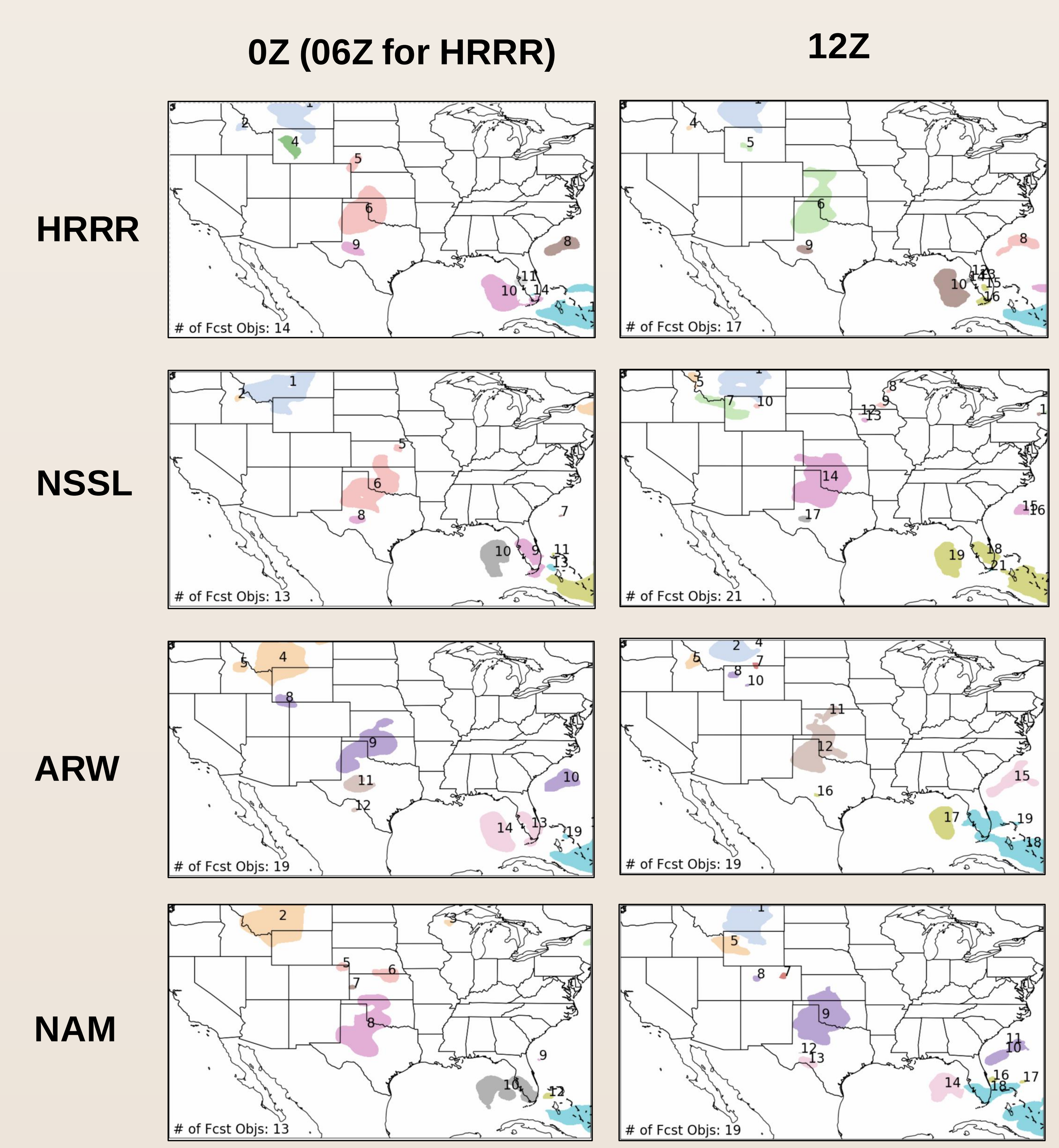


Histograms showing the distributions of displacement errors (in km) in the east/west and north/south directions. In this member, there is a slight tendency towards eastward displacement errors.

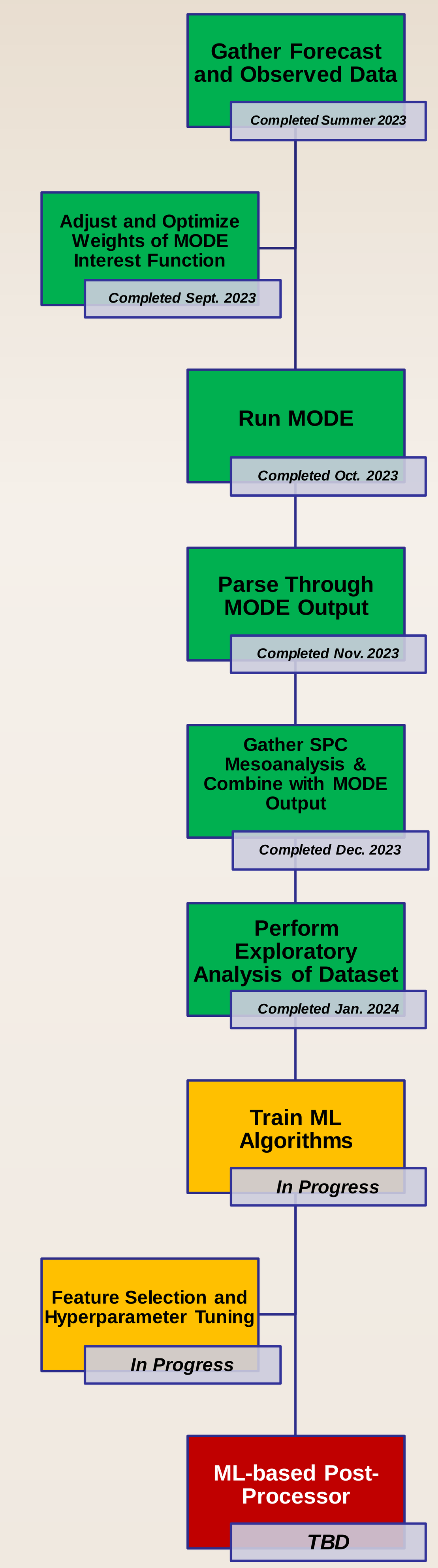


Event of interest is object 12. MCS traveled from the Texas Panhandle to S. Central Texas.

MODE Output Example Case: June 3, 2023



Progress Overview



Future Work

- **Functional ML-based post-processing tool**
  - Prototype to be tested at FFaIR experiment
  - Verification via application to the Flooded Locations and Simulated Hydrographs (FLASH) system
- **Develop guidance for Weather Prediction Center to apply tool to forecasts**