Ph.D. Defense Announcement
Gregory Herman
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Ph.D. Defense

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Defense
ATS Large Classroom (101 ATS)

Post Defense Meeting
Riehl Conference Room (211 ACRC)

Committee:
Russ Schumacher (advisor)
Susan van den Heever
Elizabeth Barnes
Thomas Hamill (NOAA)
Daniel Cooley (Statistics)

A New Post-Processing Paradigm? Improving High-Impact Weather Forecasts with Machine Learning

High-impact weather comes in many different shapes, sizes, environments, and storm types, but all pose threats to human life, property, and the economy. Because of the significant societal hazards inflicted by these events, having skillful forecasts of the risks with sufficient lead time to make appropriate precautions is critical. In order to occur, these extreme events require a special conglomeration of unusual meteorological conditions. Consequently, effective forecasting of such events often requires different perspectives and tools than routine forecasts. A number of other factors make advance forecasts of rare, high-impact weather events particularly challenging, including the lack of sufficient resolution to adequately simulate the phenomena dynamically in a forecast model; model biases in representing storms; and even difficulty in defining and verifying the high-impact event. The dissertation systematically addresses these recurring challenges for several types of high-impact weather: flash flooding and extreme rainfall, tornadoes, severe hail, and strong convective winds. For each, research is conducted to more concretely define the current state of the science in analyzing, verifying, and forecasting the phenomenon. This seminar focuses on the investigation into extreme rainfall.

Flash flooding is a notoriously challenging forecast problem, but the challenge is rooted even more fundamentally with difficulties in assessing and verifying flash flooding from *observations* due to the complex combination of hydrometeorological factors affecting flash flood occurrence and intensity. The first study discussed investigates the multi-faceted flash flood analysis problem from a simplified framework considering only quantitative precipitation estimates (QPEs) to assess flash flood risk. Many different QPE-to-flash flood potential frameworks and QPE sources are considered over a multi-year evaluation period and QPE exceedances are compared against flash flood observations and warnings. No conclusive “best” flash flood analysis framework is clearly identified, though specific strengths and weaknesses of different approaches and QPE sources are identified along with regional differences in optimal correspondence with observations.

After examining extreme rainfall and flash flooding from an observations standpoint, the next two-part study accompanies the flash flood analysis investigation by approaching *forecasting* challenges associated with extreme precipitation. In particular, more than a decade of forecasts from a convection-parameterized global ensemble, the National Oceanic and Atmospheric Administration’s Second Generation Global Ensemble Forecast System Reforecast (GEFS/R) model, are used to develop machine learning (ML) models for probabilistic prediction of extreme rainfall across the conterminous United States (CONUS) at Days 2 and 3. Both random forests (RFs) and logistic regression models (LR) are developed, with separate models trained for each lead time and for eight different CONUS regions. Models use the spatiotemporal evolution of a host of different atmospheric fields as predictors in addition to select geographic and climatological predictors. The models are evaluated over four years of withheld forecasts. The models, and particularly the RFs, are found to compare very favorably with both raw GEFS/R ensemble forecasts and those from a superior global ensemble produced by the European Centre for Medium-Range Weather Forecasts (ECMWF) both in terms of forecast skill and reliability. The trained models are also inspected to discern what statistical findings are identified through ML. Many of the findings quantify anecdotal knowledge that is already recognized regarding the forecast problem, such as the relative skill of simulated precipitation in areas where extreme precipitation events are associated with large-scale processes well resolved by the GEFS/R compared with areas where extreme precipitation predominantly occurs in association with convection in the warm-season. But more subtle spatiotemporal biases are also diagnosed, including a northern displacement bias in the placement of convective systems and a southern displacement bias in placing landfalling atmospheric rivers.

The seminar will conclude with brief discussion of the generalizability of these models in forecast operations, and on how these methods can be directly used to improve operational forecasting. Overall, multiple high-impact weather phenomena—extreme precipitation and severe weather—are investigated from verification, analysis, and forecasting standpoints. On verification and analysis, foundations have been laid both to improve existing operational products as well as better frame and contextualize future studies. ML post-processing models developed were highly successful in advancing forecast skill and reliability for these hazardous weather phenomena despite being developed from predictors of a coarse, dated dynamical model in the GEFS/R. The findings also suggest adaptability across a wide array of forecast problems, types of predictor inputs, and lead times, raising the possibility of broader applicability of these methods in operational numerical weather prediction.