Prediction of Tropical Cyclone Intensity Forecast Error

Kieran T. Bhatia, David S. Nolan, Andrea B. Schumacher

This project is supported by the NOAA Joint Hurricane Testbed.

IHC Presentation
03-04-2014

Project Outline

- **Real-time guidance of intensity forecast error**

- Situation-dependent, unequally weighted multimodel ensemble

Motivation

- Bhatia and Nolan (2013) showed that model forecast error is often related to the nature of the particular storm and surrounding atmospheric environment

- Parameters representing initial condition error and atmospheric stability (“proxies”) are also linked to forecast error

- These proxies and environmental conditions can serve as independent variables in a regression formula to predict intensity forecast error

Methodology: Multiple Linear Regression

- $y = \beta_1 * x_1 + \beta_2 * x_2 + \ldots + \beta_M * x_M + \mu$

where β's are different weighting coefficients, x's are the different predictors, y is the dependent variable, M is the number of predictors, and μ is an intercept included to account for model biases

- 2007-2011 hurricane seasons = training period
- 2012 hurricane season = verification period
- Predictors (independent variables) are the synoptic variables and proxies for initial condition error and atmospheric stability
- Dependent variable is AE

Methodology: Multiple Linear Regression

- Dependent and independent variables are normalized so the regression coefficients for different variables and forecast intervals can be compared

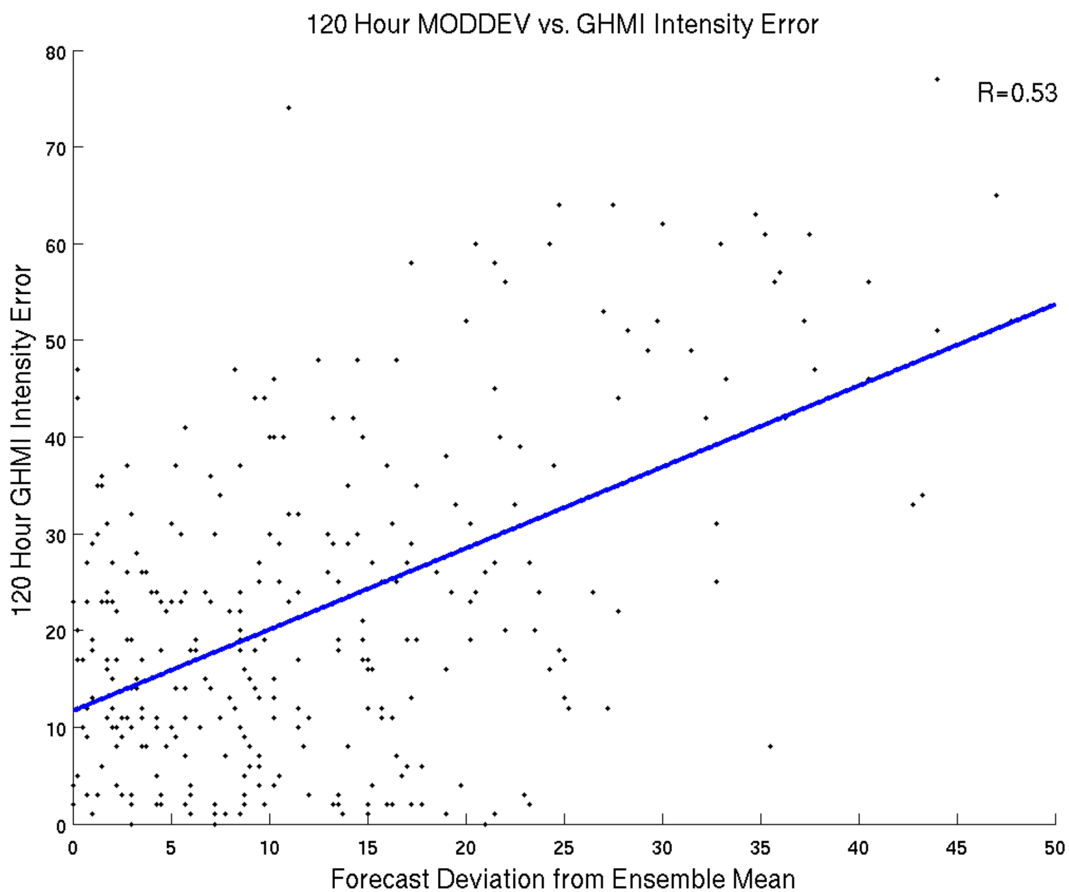
- Separate regressions performed at each forecast interval (24, 48, …, 120 hr) for each model

- Backward-stepping used: predictor is used in regression model if the probability that the regression coefficient is different from zero exceeds 95% (F statistic)

Data Used: Error Predictions

Dataset Detail	Data Used
Hurricane Seasons	2007-2012 (Atlantic Basin)
Forecast Hours	24, 48, 72, 96, and 120
Models Evaluated	LGEM, DSHP, HWFI, and GHMI ("early" models)
Predictors	**Dynamical Predictors**: Initial and forecast intensity, forecast average and 0 hour: 700-500 hPa RH, 200 hPa divergence, 850 hPa vorticity, potential intensity, storm speed, latitude, shear direction, and shear magnitude (850-200 hPa) **Initial Condition Error and Atmospheric Stability**: Standard deviation of ensemble forecast intensity, deviation of forecast from ensemble mean, forecasted intensity change, and track forecast spread
Verification criteria	Excludes "LO", "EX", INVESTS, and forecasts including land. All models must have verification and all predictors for particular time to be included (homogeneous).

120-hour GHMI Deviation from Ensemble Mean vs. 120-hour GHMI AE



Predictor Adjustments

- Removed 0-hour and forecast average predictors:
  - Distance to land
  - Longitude
  - Previous 12-hour intensity change
  - Previous 12-hour forecast error
  - Previous 12-hour late model intensity spread
- Added 0-hour and forecast average $latitude^2$
- Replaced shear direction with sin(shear direction)

Results: Predictor List

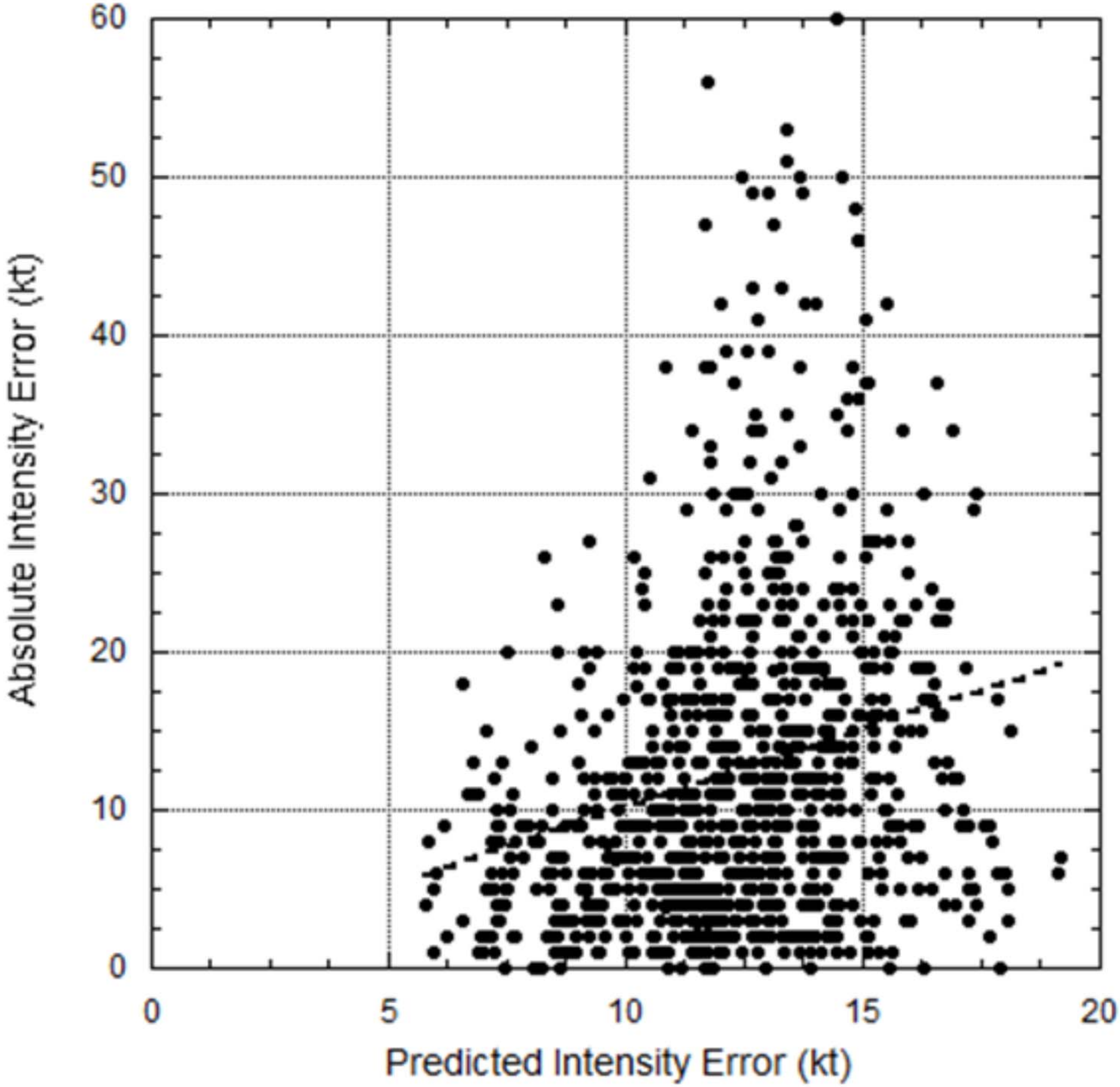
- Initial Intensity
- Forecasted Intensity
- 0-hour and Forecast Average
  - Shear
  - Storm Speed
  - MPI
  - Latitude
  - Shear Direction
  - $Latitude^2$
  - RH
  - Vorticity
  - Divergence
- Forecasted intensity change
- Early models intensity forecast spread
- Early models track forecast spread
- Deviation from intensity forecast ensemble mean

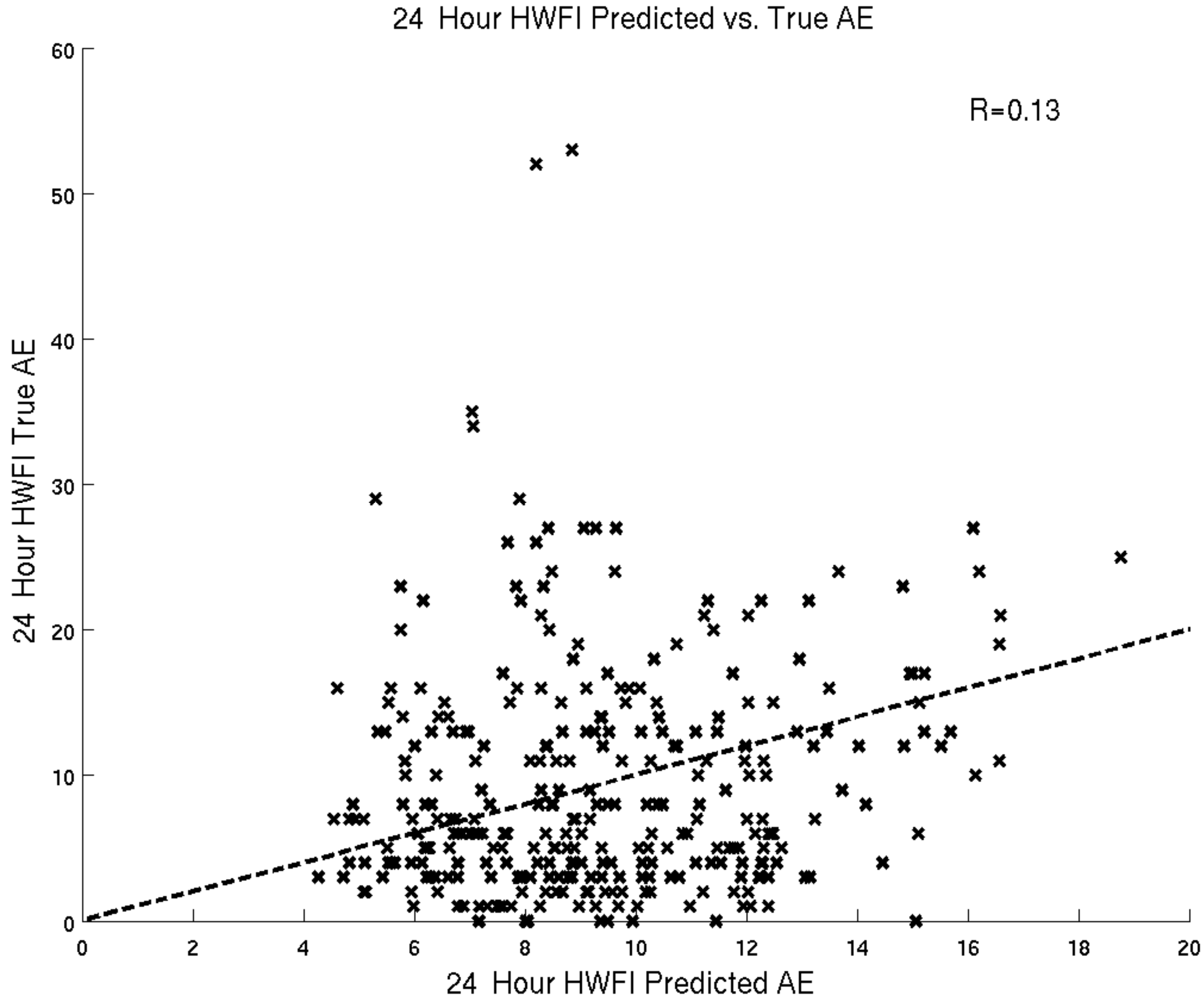
Goerss and Sampson (in press) Results

- Study focused on prediction of consensus intensity models' (IVCN and S5YY) forecast error in Atlantic and Pacific basins

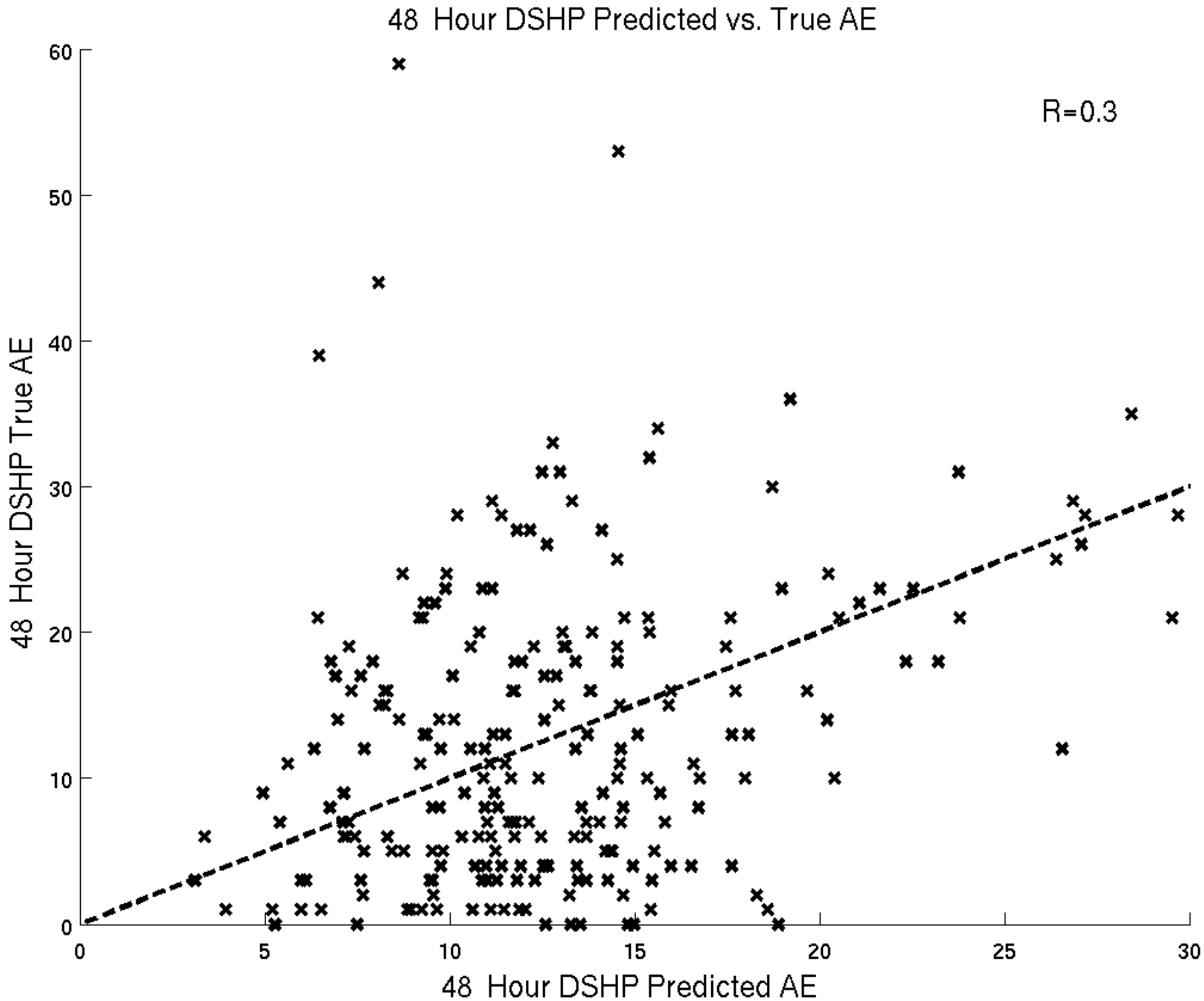
- "For the Atlantic basin, the percent variance of IVCN TC absolute intensity forecast error that could be explained for this independent sample ranged from 2-5% compared with 4-6% for the dependent sample"

IE = 0.081*INTF – 0.267*LATI + 12.6 (R=.248)

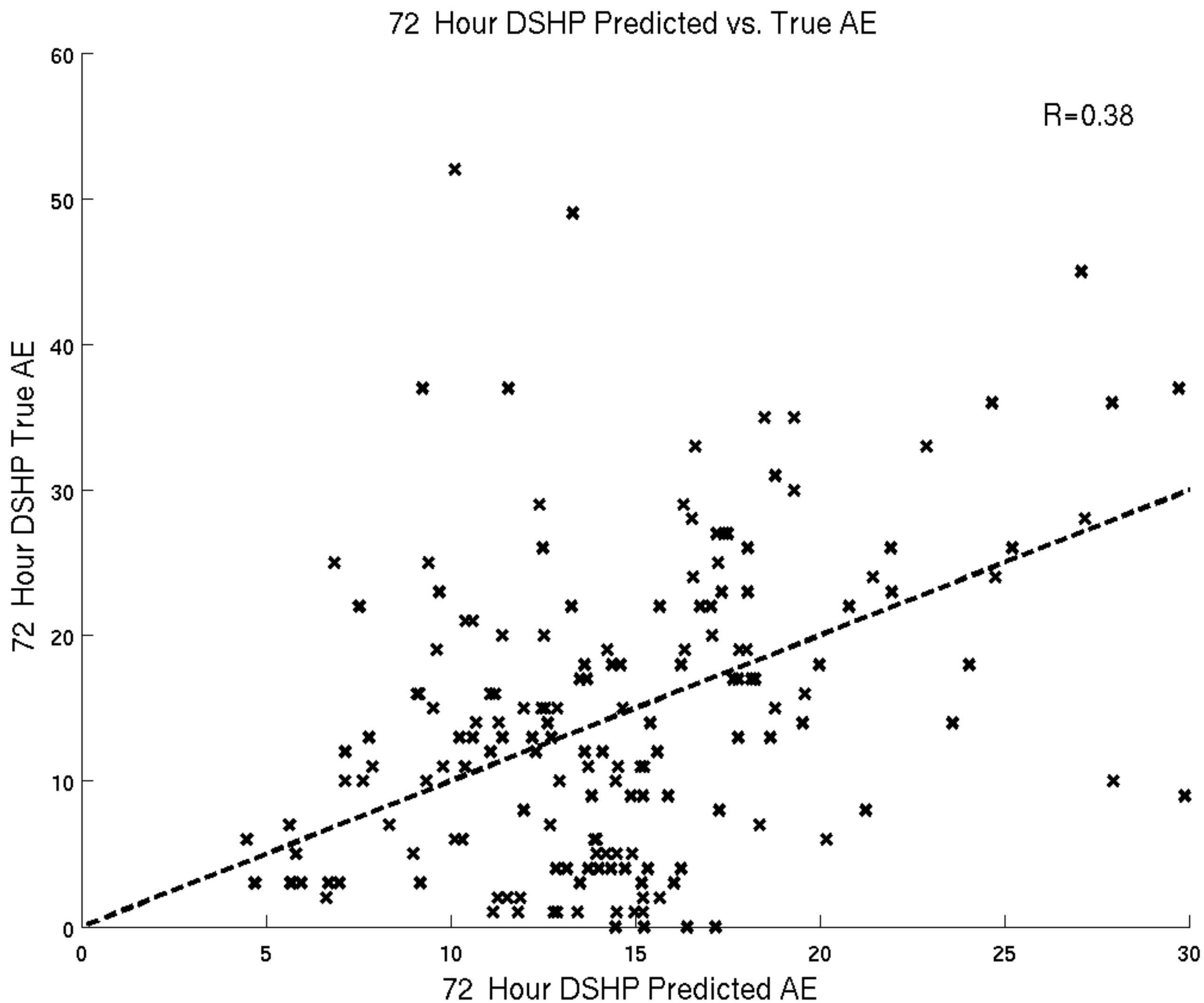




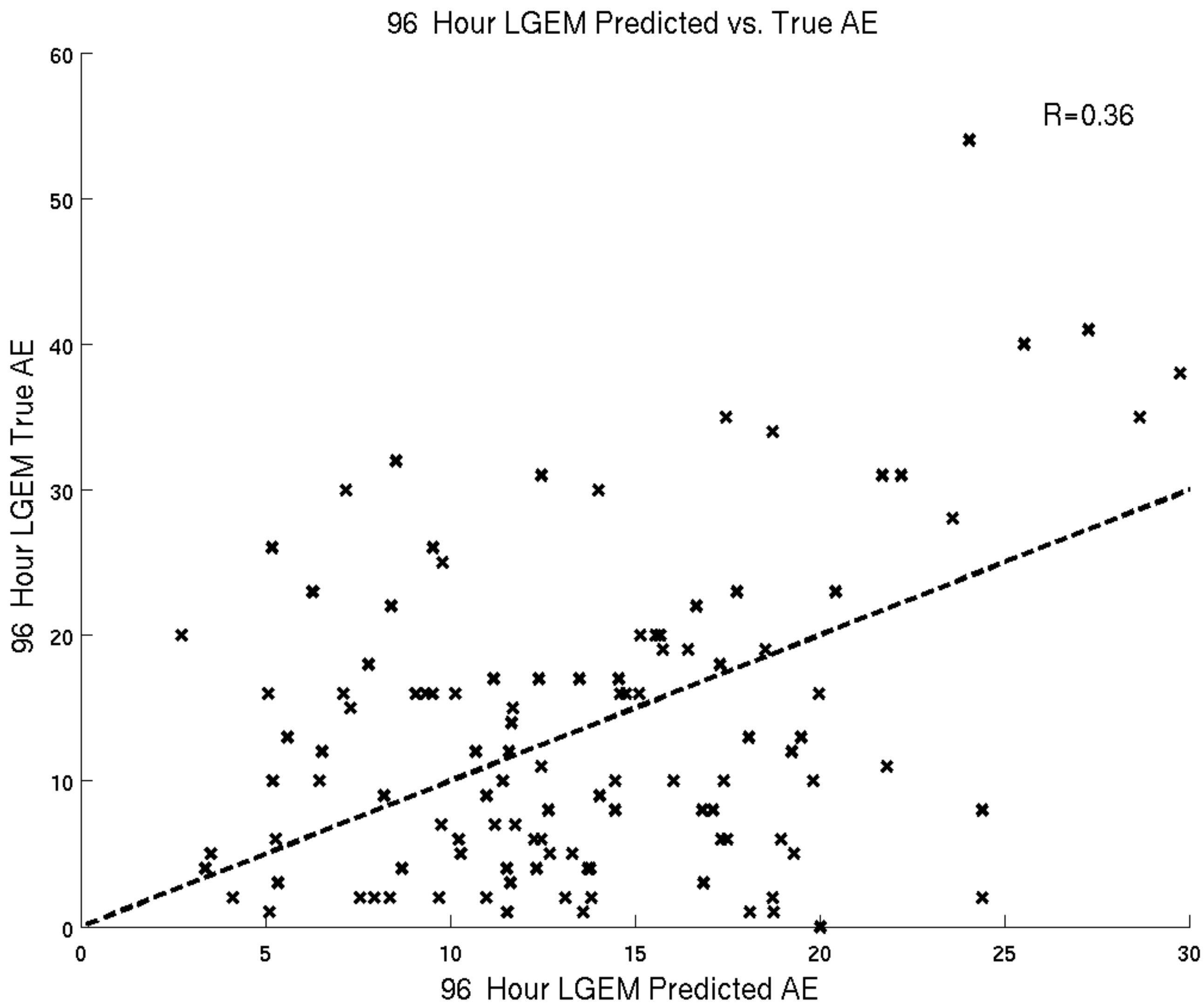
Absolute Error = 0.11 X (Fcst Int) – 0.10 X (0 hr Lat^2) – 0.11 X (Fcst Shr) + 0.24 X (Dev From Ensemble Mean)



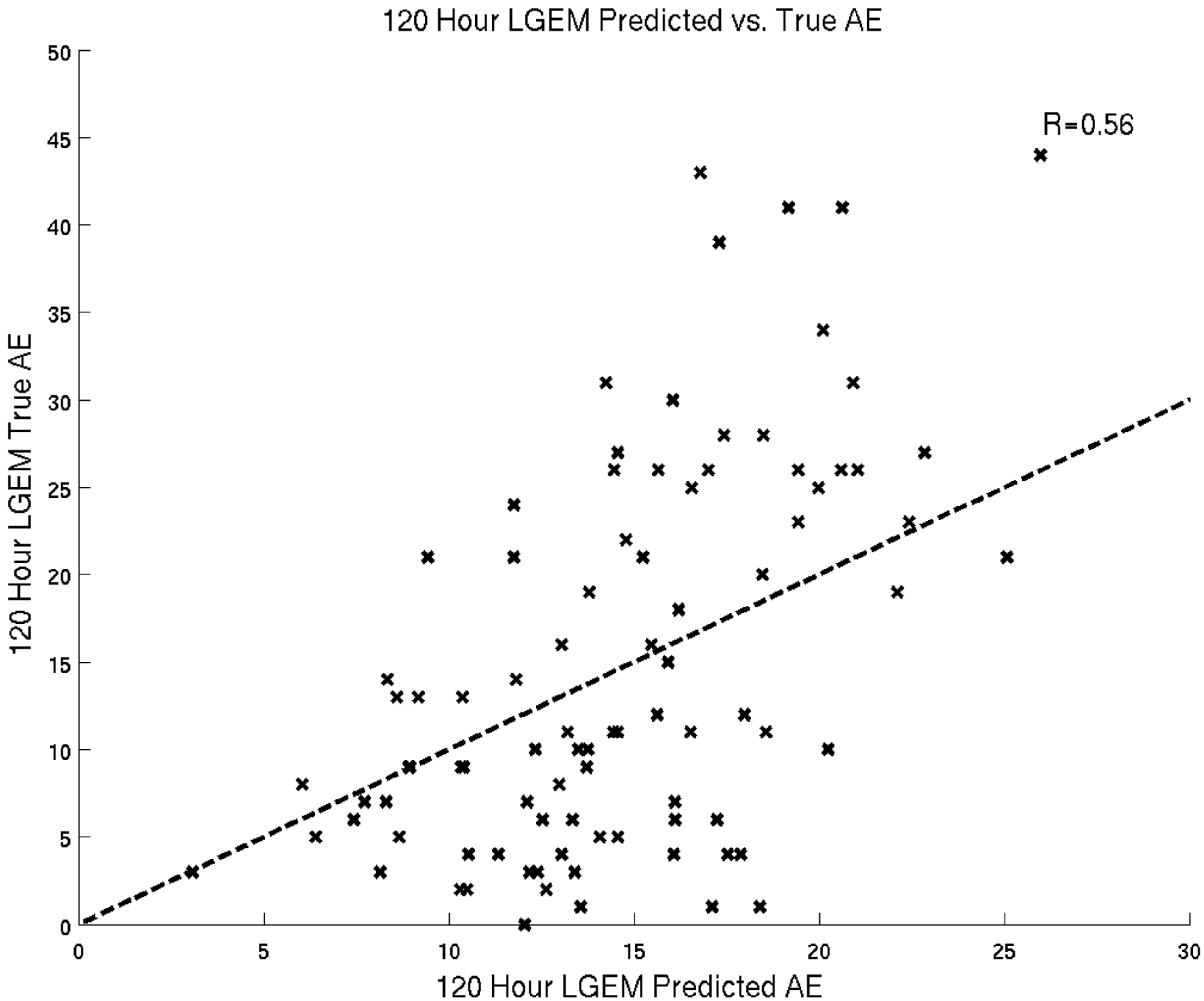
Absolute Error = 0.2 X (Fcst Int) + 0.2 X (0 hr Shr Dir) - 0.12 X (Fcst Shr Dir) – 0.24 X (Fcst Vort) + 0.23 X (0 hr Vort) + 0.17 X (Fcst Int Spread) + 0.18 X (Dev From Ensemble Mean)



Absolute Error = 0.19 X (Fcst Int) - 0.17 X (Fcst Div) – 0.16 X (Fcst Lat) + 0.19 X (Fcst Stm Spd) – 0.15 (0 hr Stm Spd) + 0.11 X (Fcst MPI) + 0.21 X (Dev From Ensemble Mean)



Absolute Error = - 0.29 X (0 hr Stm Spd) + 0.11 X (0 hr Shr) - 0.42 X (0 hr RH) + 0.10 X (Fcst MPI) + 0.24 X (Fcst Stm Spd) - 0.33 X (Fcst Lat) - 0.38 X (Fcst Div) + 0.54 X (Fcst RH) + 0.18 X (Fcst Shr Dir) – 0.12 X (Fcst Sprd) + 0.25 X (Dev From Ens Mean)



Absolute Error = -0.21 X (0 hr Int) + 0.16 X (0 hr Shr) - 0.18 X (0 hr MPI) + 1.58 X (0 hr Lat) – 1.09 (0 hr Sqr Lat) + 0.28 X (0 hr Div) – 0.30 X (0 hr Stm Spd) - 0.54 X (0 hr RH) - 0.80 X (Fcst Lat) - 0.25 X (Fcst Div) + 0.23 X (Fcst Stm Spd) + 0.40 X (Fcst RH)

Conclusions

- 24-member predictor pool selected using results of Bhatia and Nolan (2013) and inputted into a multiple linear regression model
- Predictor coefficient weights sometimes contradict physical intuition
- Multiple linear regression techniques shows promise with R^2 ranging from 0.01-0.31

Future Work

- Testing more proxies
- Developing nonlinear relationships between predictors and forecast error
- Varying the length of training period
- Producing error predictions using probabilistic forecasts
- Neural networking and nonlinear regression methods may be considered