

# Guidance on Intensity Guidance

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IHC Presentation  
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# Project Outline

- Real-time guidance of intensity forecast error
- Applications of error predictions

# Project Motivation

- Bhatia and Nolan (2013) showed that intensity 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.

# Data Sample

Dataset Detail	Data Used
Hurricane Seasons	2007-2013 (Atlantic Basin)
Forecast Hours	12-120 (12-hour increments)
Models Evaluated	LGEM, DSHP, HWFI, and GHMI
Predictors	GFS output obtained from SHIPS text files and proxies
Verification criteria	Excludes “LO”, “EX”, and INVESTS. All models must have verification and all predictors for particular time to be included (homogeneous). Land and no land cases combined.

# Dynamical Predictors

- Initial and forecast intensity
- Initial % GOES Cold Pixels
- GOES IR Brightness Temperature
- Forecast average and 0 hour:
  - 700-500 hPa RH
  - 200 hPa divergence
  - 850 hPa vorticity
  - Potential intensity
  - Storm speed
  - Latitude
  - Longitude
  - Sin(shear direction)
  - Shear magnitude (850-200 hPa)
  - Ocean heat content

# Initial Condition Error and Atmospheric Stability Predictors:

- Standard deviation of ensemble forecast intensity
- Deviation of the intensity forecast from ensemble mean (absolute value for AE)
- Deviation of the track forecast from ensemble mean
- Forecasted intensity change (absolute value for AE)
- Previous 12-hour intensity change
- Previous 12-hour error
- Initial and forecasted distance to land

# Methodology: Multiple Linear Regression

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

- Independent variables (x's) are proxies and synoptic parameters
- Dependent variable (y) is absolute error (AE) or bias
- M is the number of predictors
- $\mu$  is an intercept included to account for model biases

# Methodology: Multiple Linear Regression

- Dependent and independent variables are normalized
- Separate regressions performed for each forecast interval (12, 24, ..., 120 hr), model, and training period
- Backward-stepping used: predictor is used in regression model if the probability that the regression coefficient is different from zero exceeds 95% (F statistic)
- Dependent and independent verification (cross-validated)



# Predictor and Predictand Transformations

- AE is bounded by 0, which leads to a positively skewed distribution
- Box-Cox transformation applied to AE to make it approximately Gaussian before regression is applied
- To account for non-linear relationships between predictors and forecast error, low order polynomials and Gaussian functions are applied to the predictors and tested
- For example, 0-hour relative humidity (RH) is fitted using a Gaussian to account for peak error at medium RH values

# Results

ALL RESULTS FOR INDEPENDENT  
DATASET, CROSS VALIDATION USED  
FOR 2007-2014

# R<sup>2</sup> of AE Predictions

# of Cases	Hours	DSHP	LGEM	HWFI	GHMI
1884	12	0.06	0.05	0.09	0.11
1683	24	0.07	0.07	0.06	0.10
1483	36	0.06	0.07	0.08	0.12
1297	48	0.06	0.09	0.10	0.10
1138	60	0.09	0.11	0.11	0.10
1003	72	0.11	0.13	0.15	0.11
870	84	0.18	0.16	0.18	0.10
746	96	0.26	0.16	0.15	0.12
652	108	0.24	0.10	0.17	0.17
570	120	0.23	0.12	0.20	0.19

# R<sup>2</sup> of Bias Predictions

# of Cases	Hours	DSHP	LGEM	HWFI	GHMI
1884	12	0.16	0.18	0.18	0.16
1683	24	0.24	0.23	0.22	0.22
1483	36	0.23	0.25	0.26	0.32
1297	48	0.22	0.25	0.30	0.32
1138	60	0.25	0.27	0.31	0.33
1003	72	0.28	0.29	0.35	0.33
870	84	0.32	0.28	0.38	0.31
746	96	0.36	0.26	0.40	0.31
652	108	0.37	0.22	0.43	0.28
570	120	0.39	0.24	0.46	0.34

# Percent Improvement Over AE Climatology Forecasts

Hours	DSHP	LGEM	HWFI	GHMI
12	7.7	6.1	7.7	8.9
24	9.2	7.9	8.1	8.6
36	8.3	6.3	9.5	9.7
48	6.8	6.9	11.0	10.0
60	8.5	10.0	10.0	10.8
72	10.0	10.1	11.5	9.9
84	15.0	12.5	11.5	10.4
96	17.8	11.2	10.6	12.5
108	11.9	8.1	11.0	16.0
120	10.5	9.5	12.0	18.2

# Percent Improvement Over Bias

## Climatology Forecasts

Hours	DSHP	LGEM	HWFI	GHMI
12	8.0	8.6	9.7	11.4
24	14.9	13.0	11.3	13.9
36	14.2	15.8	14.2	19.4
48	13.9	14.8	15.0	20.4
60	17.9	15.1	16.1	20.9
72	22.1	16.3	20.9	21.1
84	23.8	15.4	23.1	18.6
96	25.7	12.3	25.1	16.6
108	25.2	9.8	26.8	15.5
120	23.2	11.0	30.2	22.8

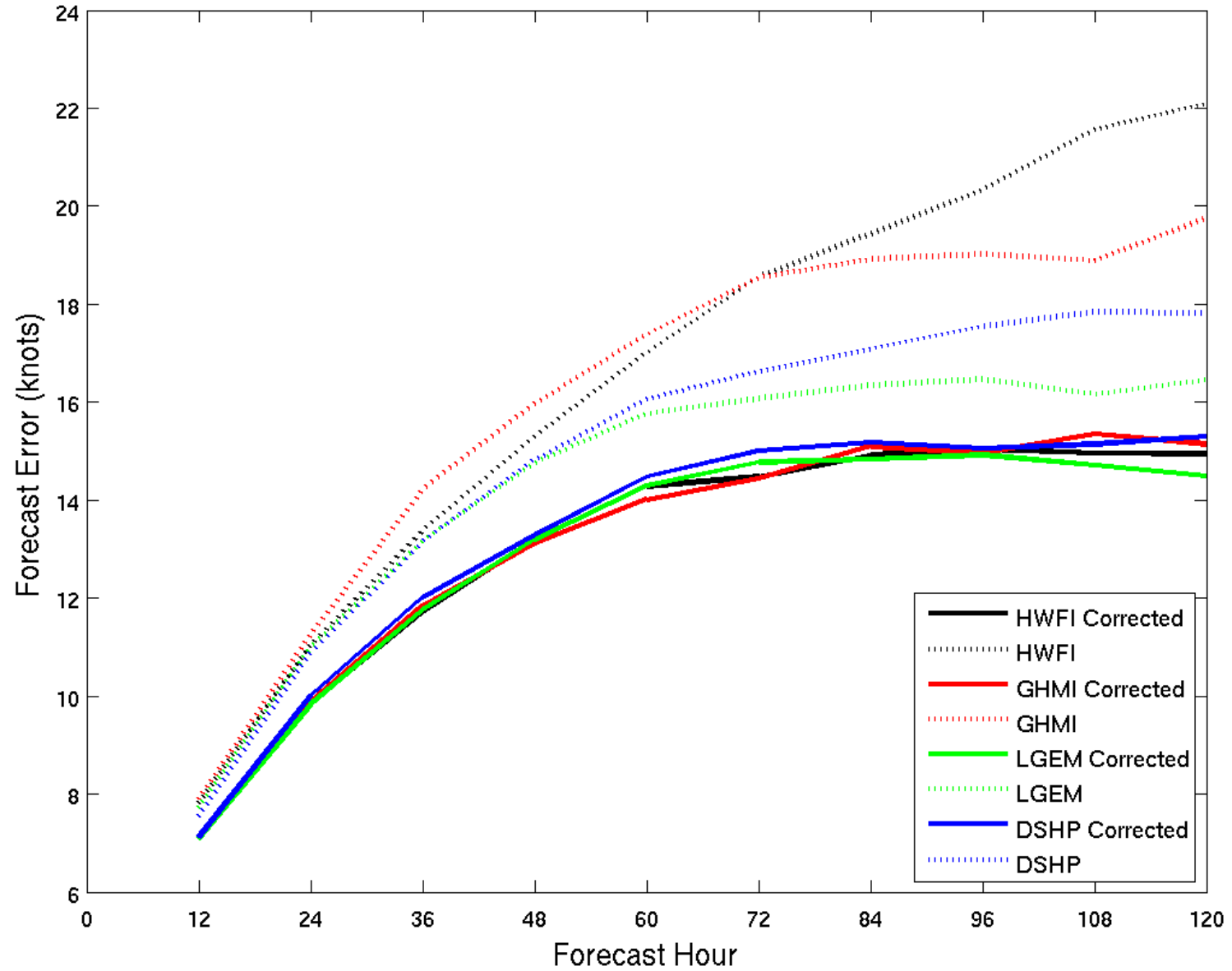
# Applications

# Motivation

- If model error can be successfully anticipated in certain situations, can we bias-correct the models or weight an ensemble accordingly?
- Two first attempts to create unequally weighted ensembles can be derived from AE and bias predictions.



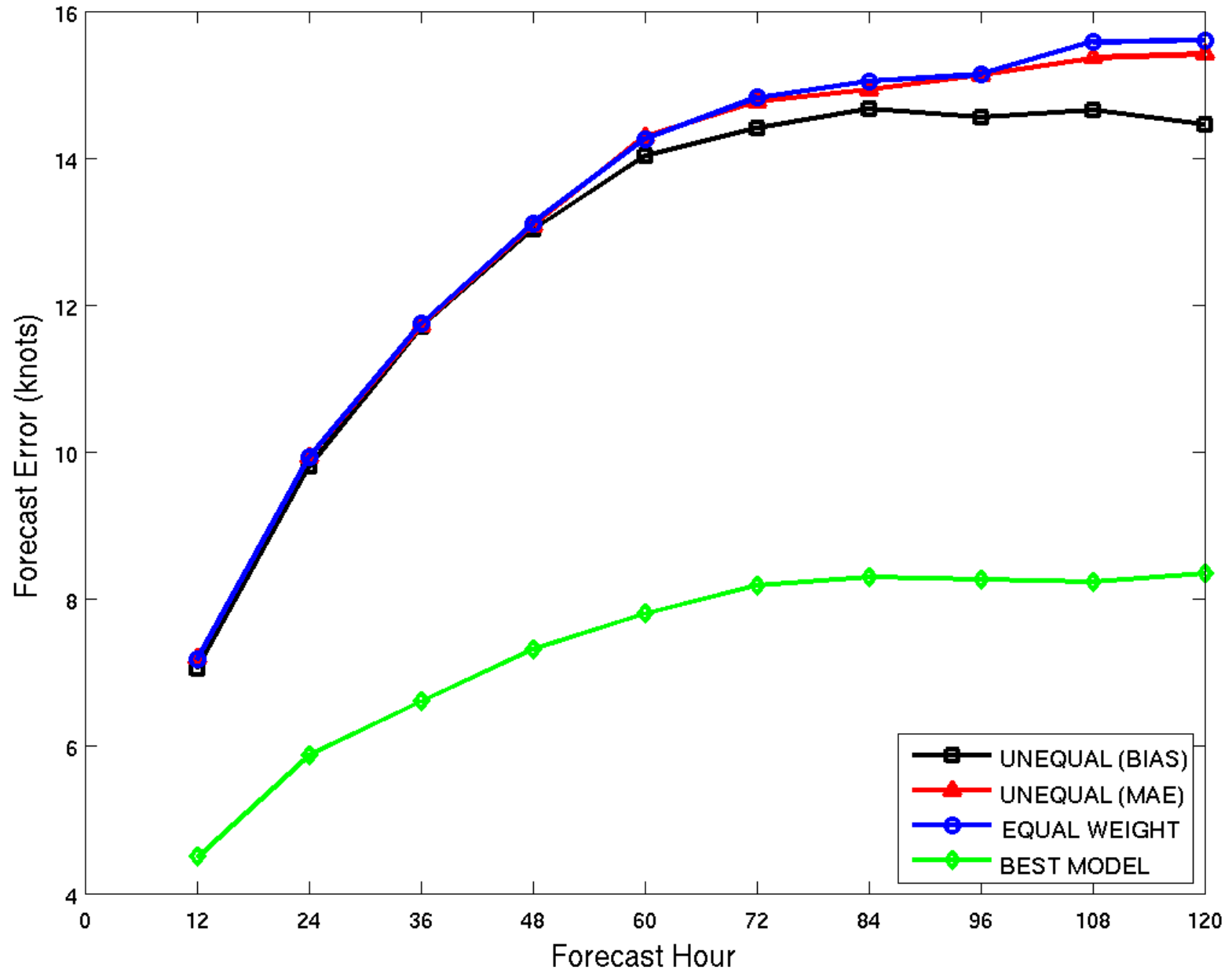
## 2007-2013 Bias-Corrected Model Comparison



# Methodology For Unequally Weighted Ensemble

- Technique 1
  - Bias-correct individual models using bias forecasts and use the mean of the bias-corrected models
- Technique 2
  - Inverse-weight individual models using AE forecasts and use the inverse-weighted average as the ensemble mean
  - i.e. if LGEM is predicted to have 20 knots of AE and DSHP is predicted to have 10 knots of AE, trust DSHP's forecast more

## 2007-2013 Multimodel Ensemble Comparison



# Conclusions

- Predictor pool selected using results of Bhatia and Nolan (2013) and added proxies
- Inputted into a modified multiple linear regression model
- Multiple linear regression techniques are promising with 2007-2014 independent results showing percent improvement over climatology ranging from 6%-18% for AE and 8%-30% for bias

# Extra Slides

# Future Work

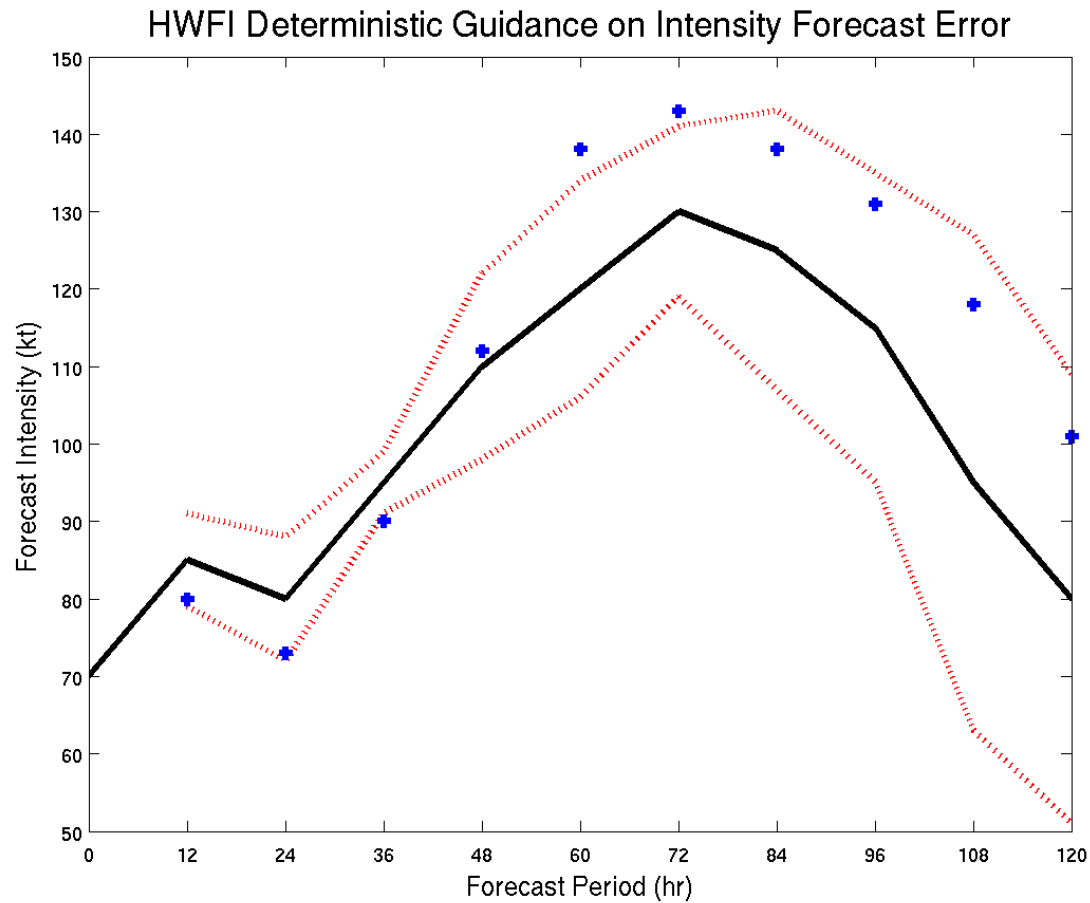
- Testing more proxies
- Developing nonlinear relationships between predictors and forecast error
- Varying the length of training period
- Producing error predictions using probabilistic forecasts
- Neural networking and nonlinear regression methods may be considered

# Sample Output File

\* PRedicted Intensity Model Error (PRIME) \*  
 \* AL012014 07/02/14 06 UTC \*

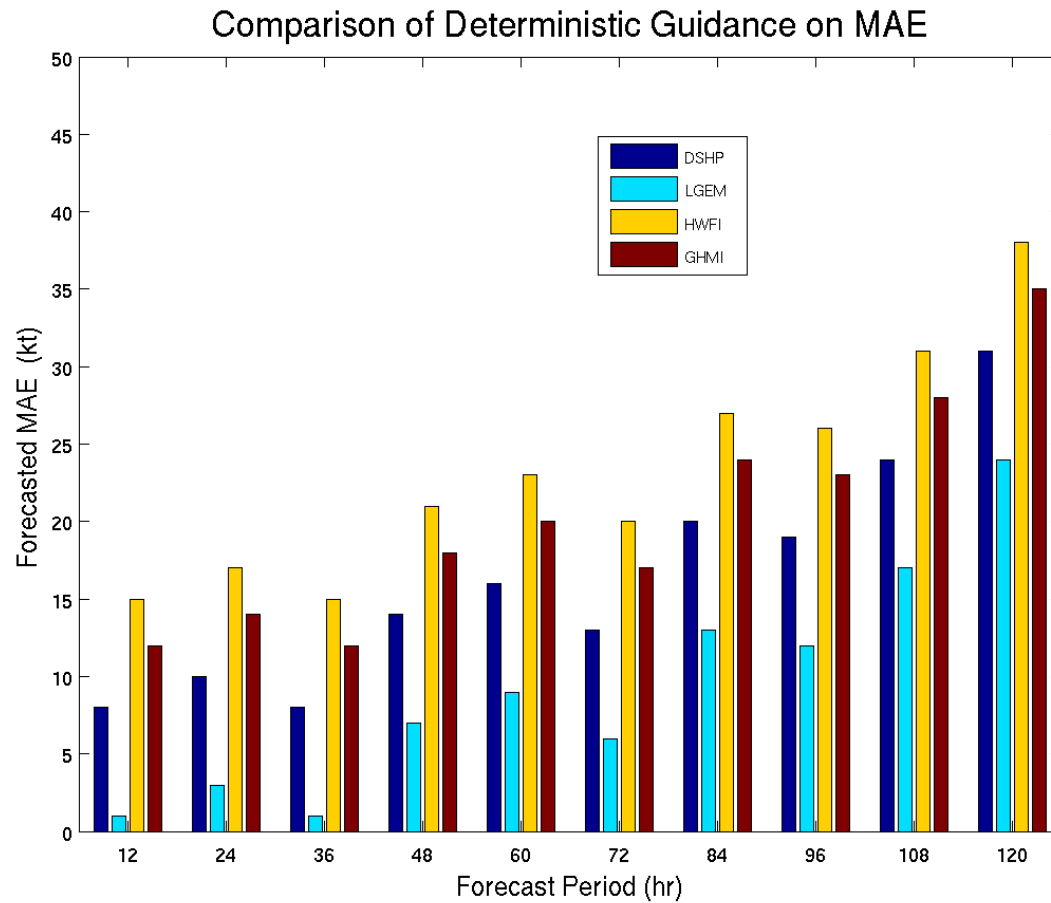
TIME	12	24	36	48	60	72	84	96	108	120
Predicted absolute error (kts):										
AERR DSHP	4.94	7.89	11.36	12.22	14.07	18.32	22.24	21.39	13.36	5.88
Predicted bias (kts):										
BIAS DSHP	0.66	2.26	5.58	6.54	8.72	12.90	20.78	23.47	16.82	4.16
AERR predictors:										
MPIA	3.37	3.35	3.36	3.35	3.33	3.28	3.20	3.11	3.02	2.94
HCTA	3.48	3.46	3.49	3.47	3.43	3.38	3.34	3.30	3.27	3.24
INTF	3.17	3.37	3.61	3.77	3.90	3.93	3.90	3.70	3.29	3.02
DV2F	1.75	3.75	6.00	6.75	8.00	11.75	18.50	20.75	15.25	5.75
SPDF	2.36	2.87	4.69	4.57	6.68	10.59	12.77	13.96	10.34	4.03
BIAS predictors:										
SPDF	2.36	2.87	4.69	4.57	6.68	10.59	12.77	13.96	10.34	4.03
LND0	-1.31	-1.31	-1.31	-1.31	-1.31	-1.31	-1.31	-1.31	-1.31	-1.31
DIVA	-1.94	-1.58	-0.73	-0.63	0.02	0.36	0.60	0.51	0.45	0.40
INTF	57.00	65.00	74.00	80.00	86.00	88.00	86.00	77.00	62.00	42.00
DV2F	1.75	3.75	6.00	6.75	8.00	11.75	18.50	20.75	15.25	5.75

# Potential Output Product 1

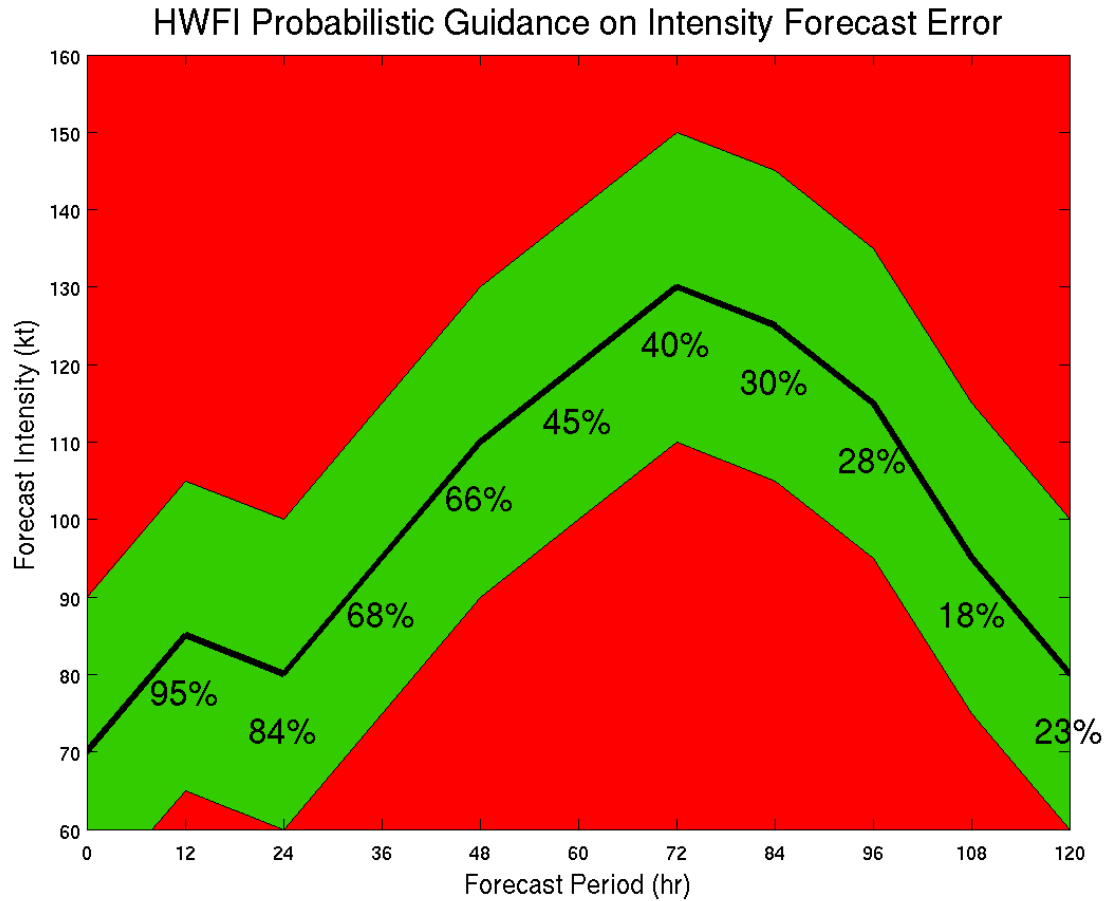




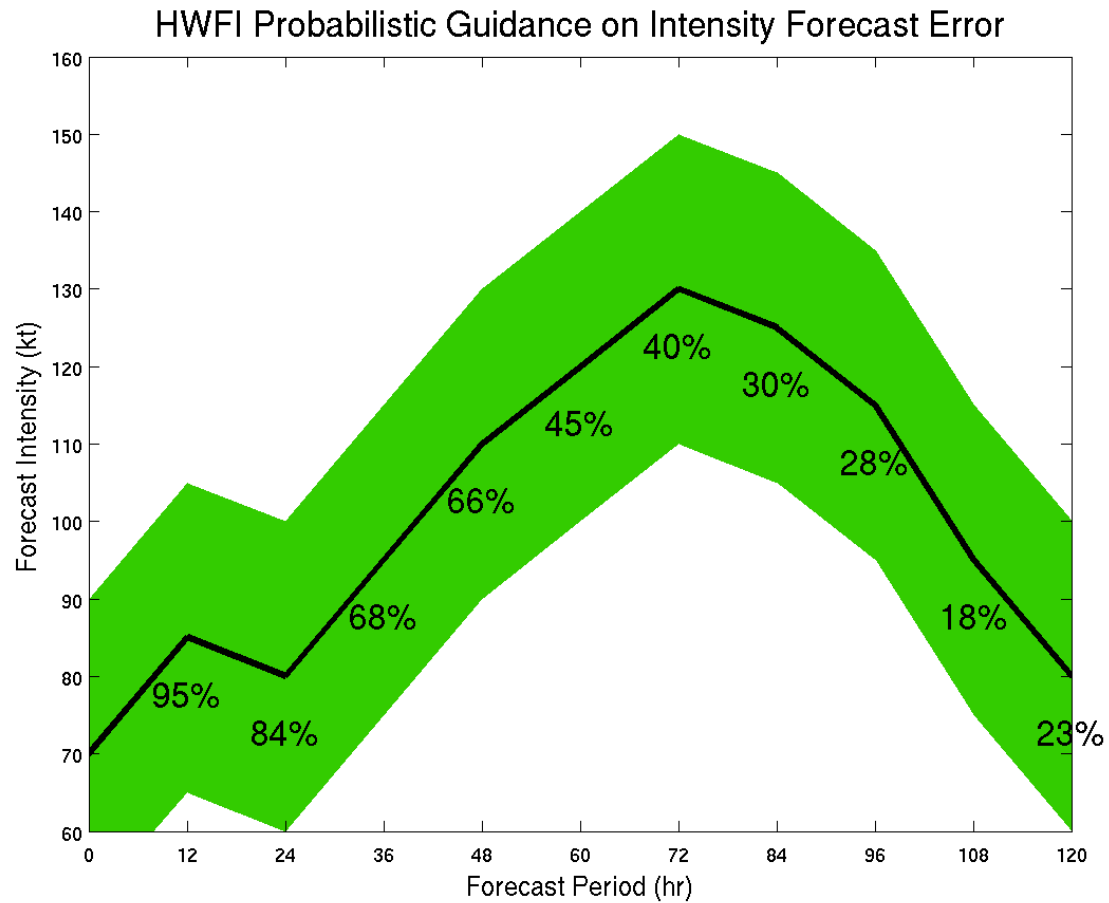
# Potential Output Product 2



# Potential Output Product 3a



# Potential Output Product 3b



# COEFFICIENT FILE

PRIME Coefficient File

DSHP

010 Forecast time

MAE

005 Predictors

FCST TIME	12	24	36	48	60	72	84	96	108	120
MAE MEAN	2.0277	2.8797	3.4720	3.6773	4.0564	3.8838	3.8257	3.8441	3.7943	3.4132
MAE STDV	0.6761	1.0300	1.3589	1.3882	1.4956	1.4338	1.4234	1.4588	1.4428	1.2053
MAE FWRI	0.00499	0.16499	0.24499	0.24999	0.27999	0.24999	0.24499	0.24999	0.23999	0.17499
MPIA GAU2	.683076	160.584	1.09840	3.49416	153.905	108.016	0.0	0.0	0.0	0.0
HCTA GAU2	2.01575	119.768	35.5479	3.60968	41.0326	83.2716	0.0	0.0	0.0	0.0
INTF POL3	-0.000129962	.00274021	-0.164705	6.06383	0.0	0.0	0.0	0.0	0.0	0.0
DV2F ABSV	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
SPDF NONE	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
MPIA MEAN	3.3714	3.3784	3.3846	3.3875	3.3965	3.3986	3.4028	3.4001	3.3967	3.3894
HCTA MEAN	3.3495	3.3624	3.3756	3.3879	3.3994	3.4088	3.4152	3.4160	3.4161	3.4119
INTF MEAN	3.2907	3.3196	3.3576	3.3960	3.4240	3.4465	3.4529	3.4475	3.4474	3.4354
DV2F MEAN	2.4509	4.1991	5.5538	6.1093	6.3410	6.5757	6.7709	6.9490	7.0488	7.5584
SPDF MEAN	3.7283	6.0581	8.0312	8.6513	9.0793	9.4785	9.8562	10.1843	10.1852	10.9127
MPIA STDV	0.2512	0.2351	0.2238	0.2110	0.2125	0.2036	0.2064	0.2066	0.2035	0.2000
HCTA STDV	0.2805	0.2634	0.2539	0.2449	0.2382	0.2351	0.2350	0.2375	0.2415	0.2460
INTF STDV	0.3417	0.3426	0.3342	0.3364	0.3432	0.3388	0.3442	0.3473	0.3469	0.3374
DV2F STDV	2.1225	3.1923	4.2029	4.5679	4.8926	5.4864	6.1965	6.8690	7.4823	7.9152
SPDF STDV	2.2674	3.2040	4.1965	4.6136	4.8186	5.3104	5.8790	6.2623	6.5822	6.9860
MPIA COEF	0.0259	0.0560	0.0629	0.0533	0.0950	0.0211	0.0130	0.0726	0.0579	0.1358
HCTA COEF	0.0691	0.0441	0.0365	0.0386	-0.0338	0.0241	0.0121	0.0267	0.0955	0.0163
INTF COEF	0.1108	0.1890	0.1925	0.1708	0.1403	0.1556	0.1741	0.2153	0.1984	0.1754
DV2F COEF	0.1271	0.1468	0.1637	0.0955	0.1333	0.1788	0.1929	0.2385	0.2727	0.2411
SPDF COEF	0.1188	0.1087	0.0805	0.1614	0.2173	0.2283	0.2686	0.2273	0.1839	0.1800

BIAS

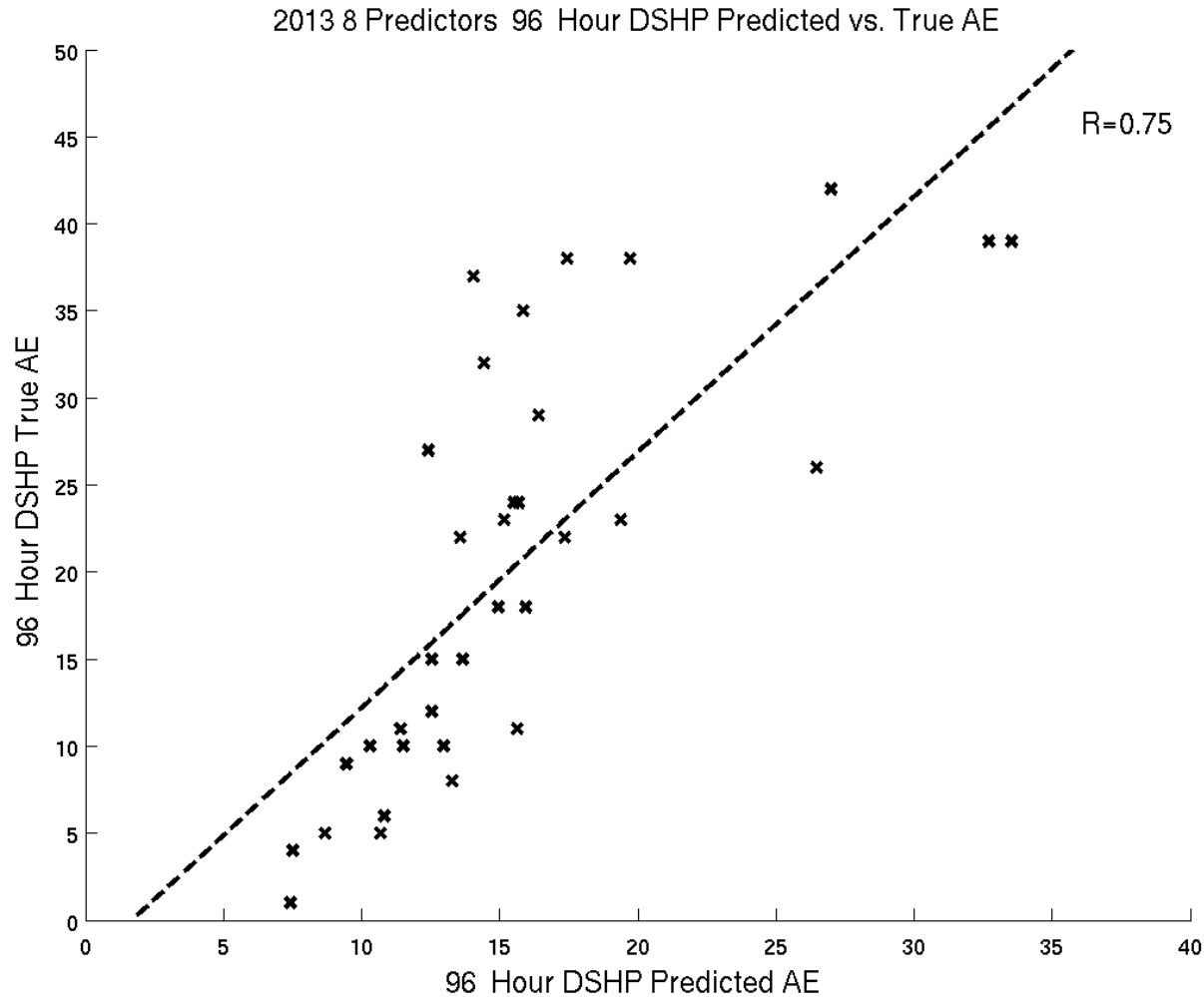
005 Predictors

FCST TIME	12	24	36	48	60	72	84	96	108	120
BIAS MEAN	-0.4243	0.6351	1.3179	1.0311	0.5900	-0.0087	-0.7496	-1.5237	-2.3320	-3.0714
BIAS STDV	9.8238	13.8507	16.3322	18.0040	19.5239	20.2618	20.1925	20.1648	20.4888	20.5265
BIAS NONE	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
SPDF NONE	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
LNDO POL2	-6.01464e-06	1.11124e-02	-2.60016e+00	0.0	0.0	0.0	0.0	0.0	0.0	0.0
DIVA POL3	-7.90620e-06	3.70410e-04	1.27796e-01	-4.26974e+00	0.0	0.0	0.0	0.0	0.0	0.0
INTF NONE	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
DV2F NONE	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
SPDF MEAN	3.7283	6.0581	8.0312	8.6513	9.0793	9.4785	9.8562	10.1843	10.1852	10.9127
LNDO MEAN	-0.2623	-0.2377	-0.2275	-0.2035	-0.1886	-0.1658	-0.1608	-0.1147	-0.0102	0.0774
DIVA MEAN	-0.0961	-0.0903	-0.1028	-0.1414	-0.1690	-0.1770	-0.2076	-0.2800	-0.3187	-0.3722
INTF MEAN	60.5718	62.6290	64.1269	64.9234	65.4455	65.3971	64.9246	63.8366	62.5508	61.0303
DV2F MEAN	0.5778	1.7094	2.3485	2.3350	2.1603	1.4554	0.5598	-0.2540	-1.3076	-2.3571
SPDF STDV	2.2674	3.2040	4.1965	4.6136	4.8186	5.3104	5.8790	6.2623	6.5822	6.9860
LNDO STDV	2.4685	2.4784	2.4548	2.4346	2.3933	2.3398	2.3275	2.2863	2.2007	2.1700
DIVA STDV	3.6838	3.5104	3.4068	3.2910	3.0971	2.9134	2.7825	2.7059	2.6117	2.5296
INTF STDV	22.8454	22.1888	21.9268	21.6192	21.6416	22.1272	22.4718	22.7929	23.2428	23.0824
DV2F STDV	3.1912	4.9916	6.5591	7.2646	7.7153	8.4429	9.1652	9.7721	10.2008	10.6928
SPDF COEF	0.0713	0.0823	0.0263	-0.0207	-0.0522	-0.0777	-0.0354	-0.0135	0.0240	0.0096
LNDO COEF	-0.0450	-0.0435	-0.0165	0.0170	0.0306	0.0532	0.0818	0.1448	0.2178	0.2396
DIVA COEF	0.0465	0.0510	0.0449	0.0616	0.0762	0.1083	0.1456	0.1831	0.1540	0.1070
INTF COEF	-0.0198	-0.0339	-0.0254	-0.0196	-0.0001	0.0132	-0.0140	-0.0475	-0.0356	0.0012
DV2F COEF	0.4212	0.5034	0.5282	0.5240	0.5286	0.5296	0.5593	0.6035	0.6260	0.6362

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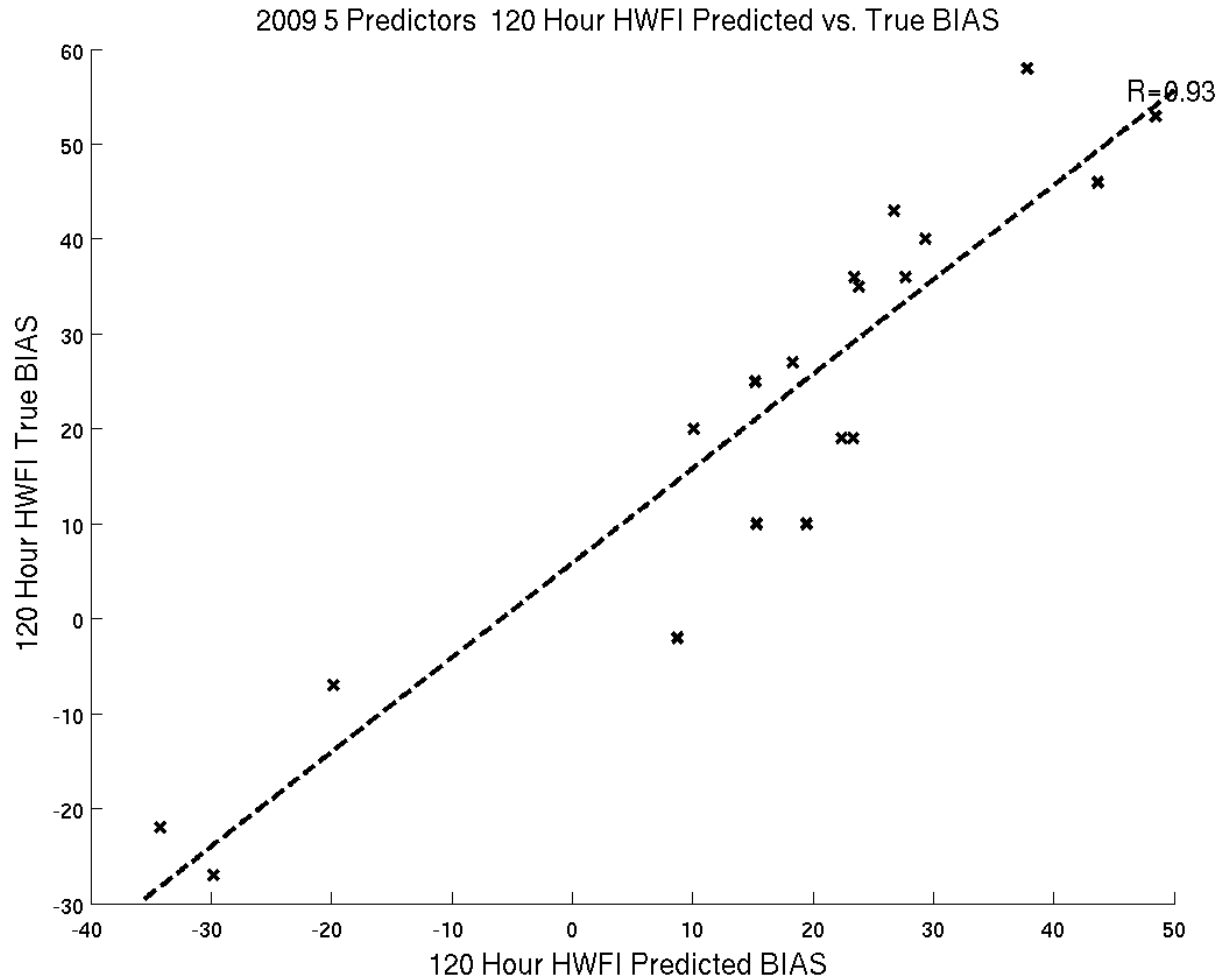
Extra details can be included here, such as...

# R=0.75, Skill Score = 31%



Absolute Error =  $-0.16 \times (\text{Avg Lat}) + 0.1 \times (\text{Prev 12 Hr Int Chng}) + 0.14 \times (\text{Abs. Val. Of Forecasted Intensity Change}) + 0.28 \times (\text{Dev From Ensemble Mean})$

# R=0.93, Skill Score = 64%

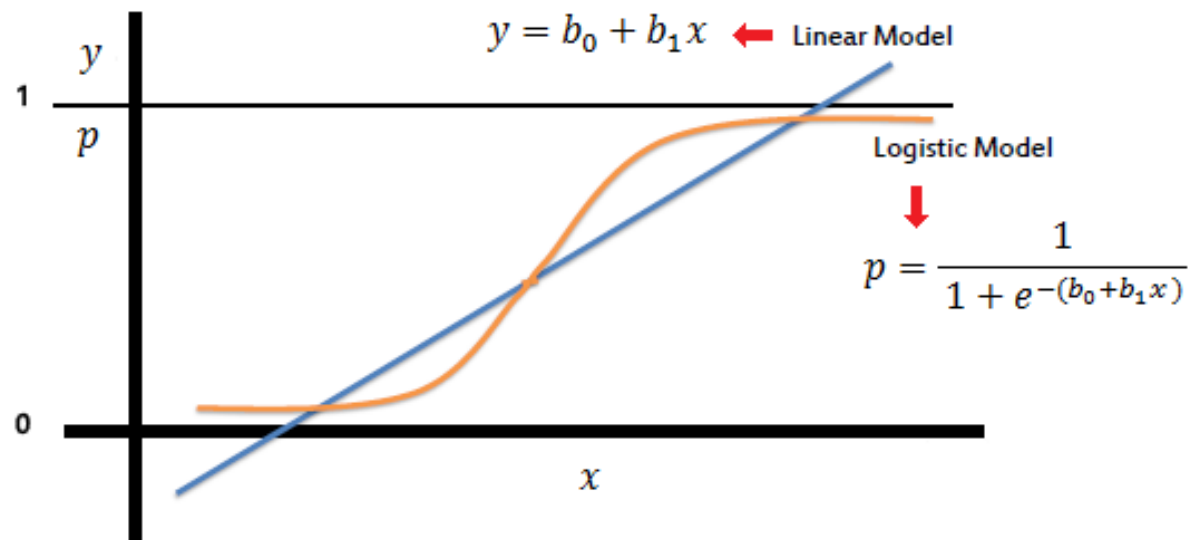


Bias = 0.14 X (0 hr Int) + 0.15 X (Avg Div) + 0.09 X (Fcst Int) + 0.57 X (Dev From Ensemble Mean)

# Probabilistic Forecasts of AE and Bias

# Logistic Regression

- Select a threshold and use to turn predictand into a binary variable
- Regression formula output is now a probability of exceeding that threshold
- $\ln\left(\frac{p_i}{1-p_i}\right) = b_0 + b_1x_1 + \dots + b_kx_k$





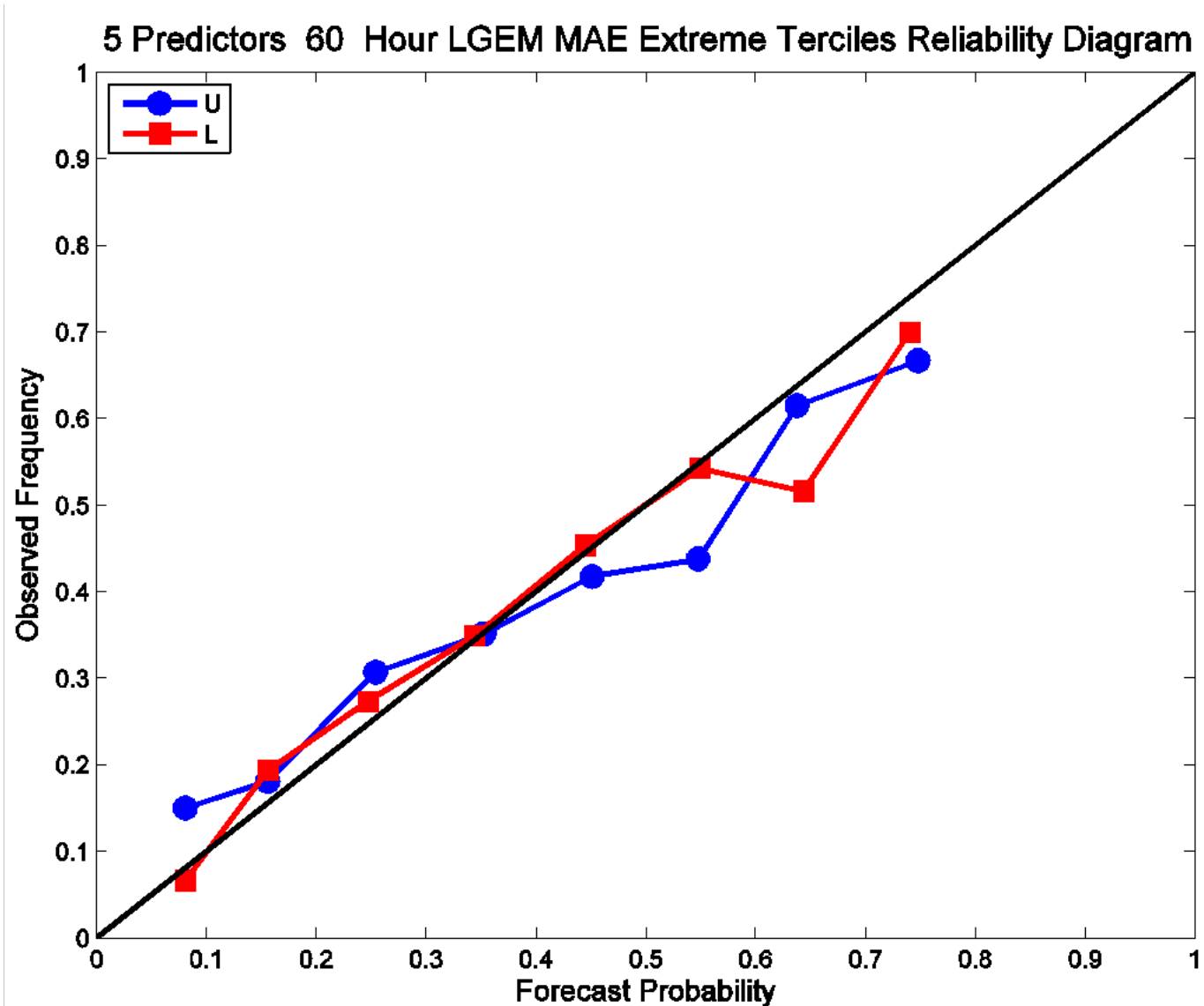
# Methodology: Probabilistic Forecasts

- AE and Bias were converted to binary and ternary variables
- AE: Binary threshold = 20 knots, Ternary thresholds= 10 knots and 20 knots
- Bias: Binary threshold = 0 knots, Ternary thresholds= -20 knots and 20 knots

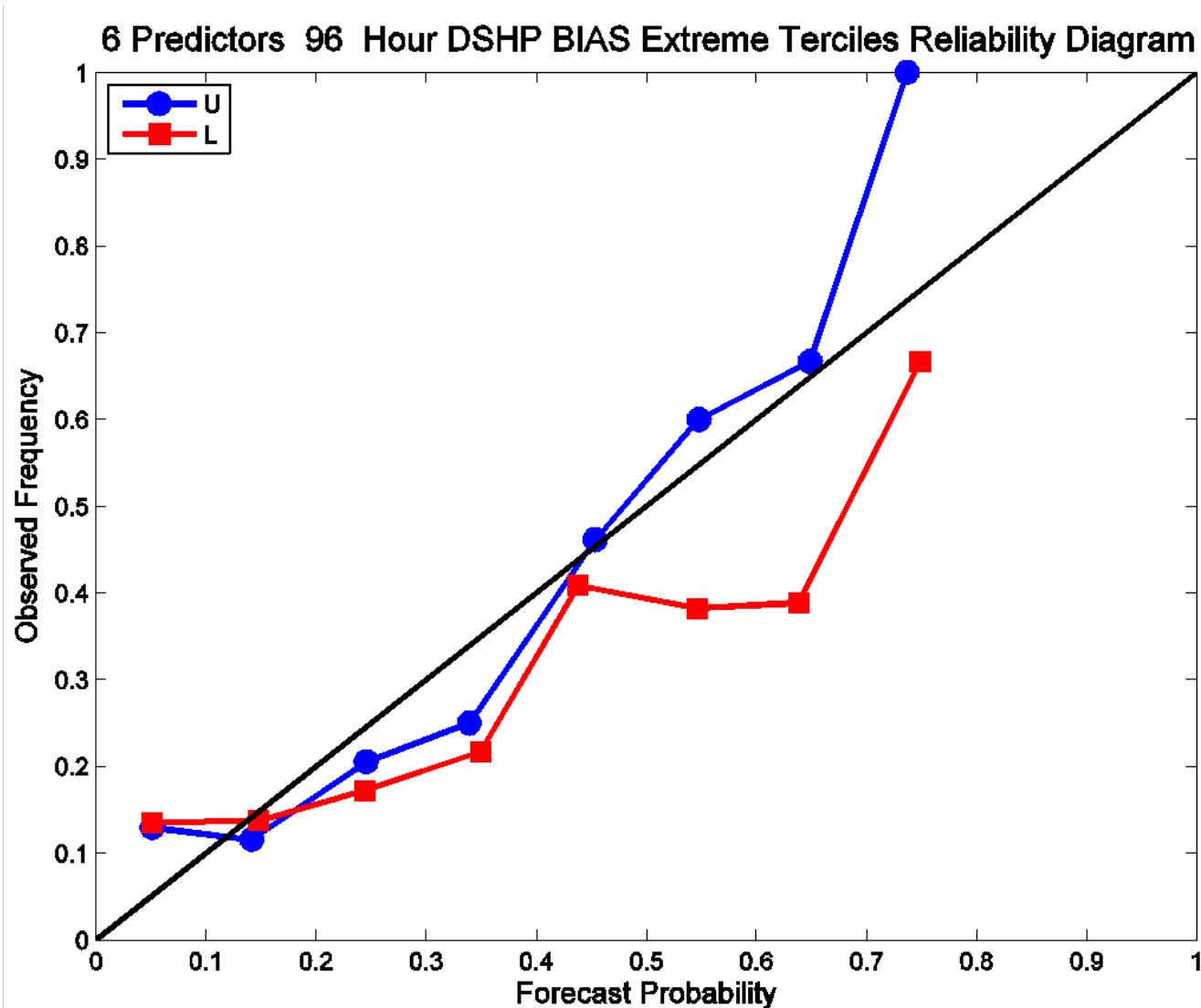
# Reliability Diagram

- Graphical device that shows the full joint distribution of the forecasts and observations
- Observed frequency of an event is plotted against the forecast probability of an event
- A perfect forecast system will result in forecasts with a probability of  $X\%$  actually occurring  $X\%$  of the time (diagonal line on the graph)

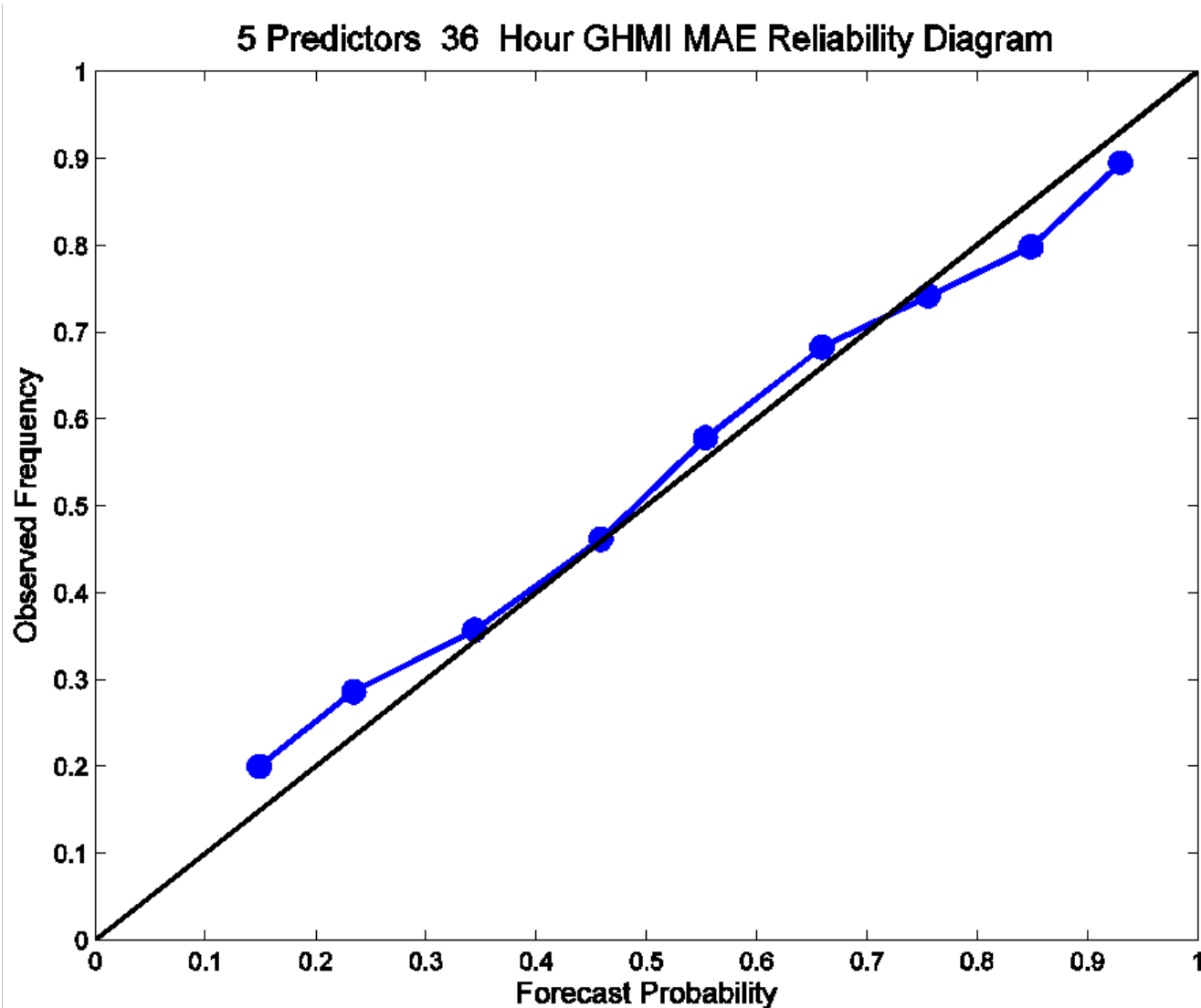
# 60-Hour LGEM AE Tercile Forecast



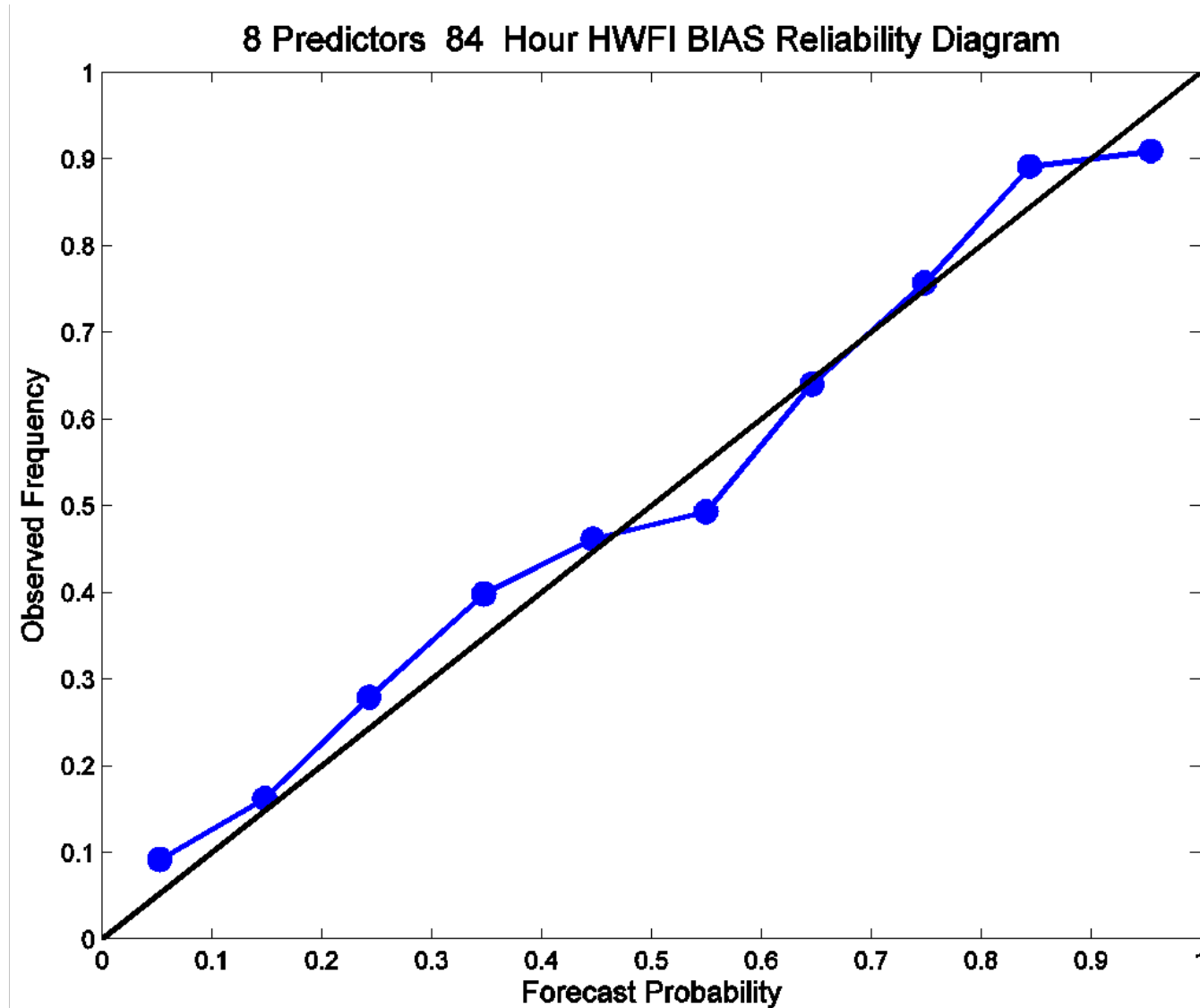
# 96-Hour DSHP BIAS Tercile Forecast



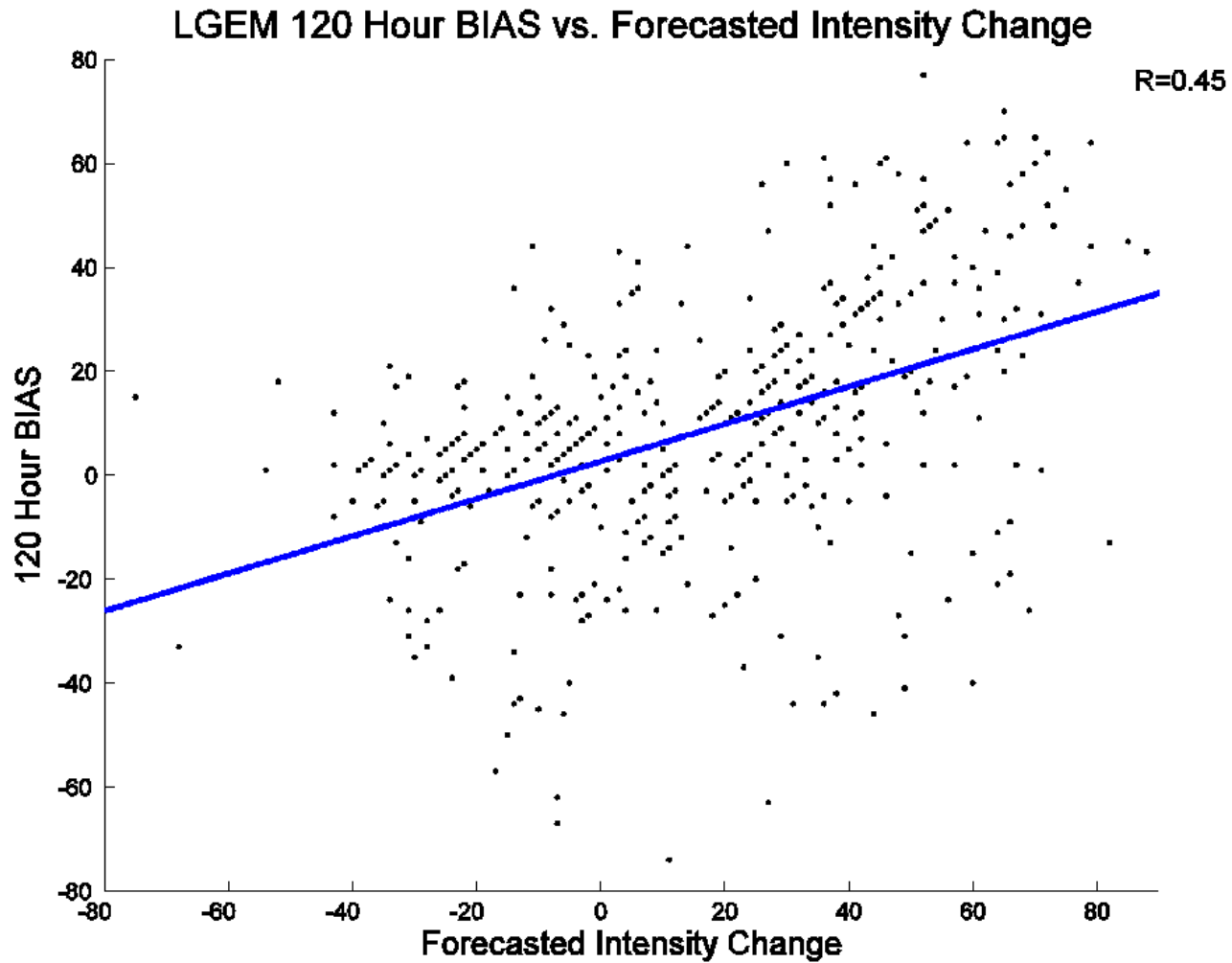
# 36-Hour GHMI AE Binary Forecast



# 84-Hour HWFI BIAS Binary Forecast



# Example of Atmospheric Instability Proxy



# Goerss and Sampson (2014) Results

## **ⓐ Prediction of Consensus Tropical Cyclone Intensity Forecast Error**

JAMES S. GOERSS

*IES, San Diego, and SAIC, Monterey, California*

CHARLES R. SAMPSON

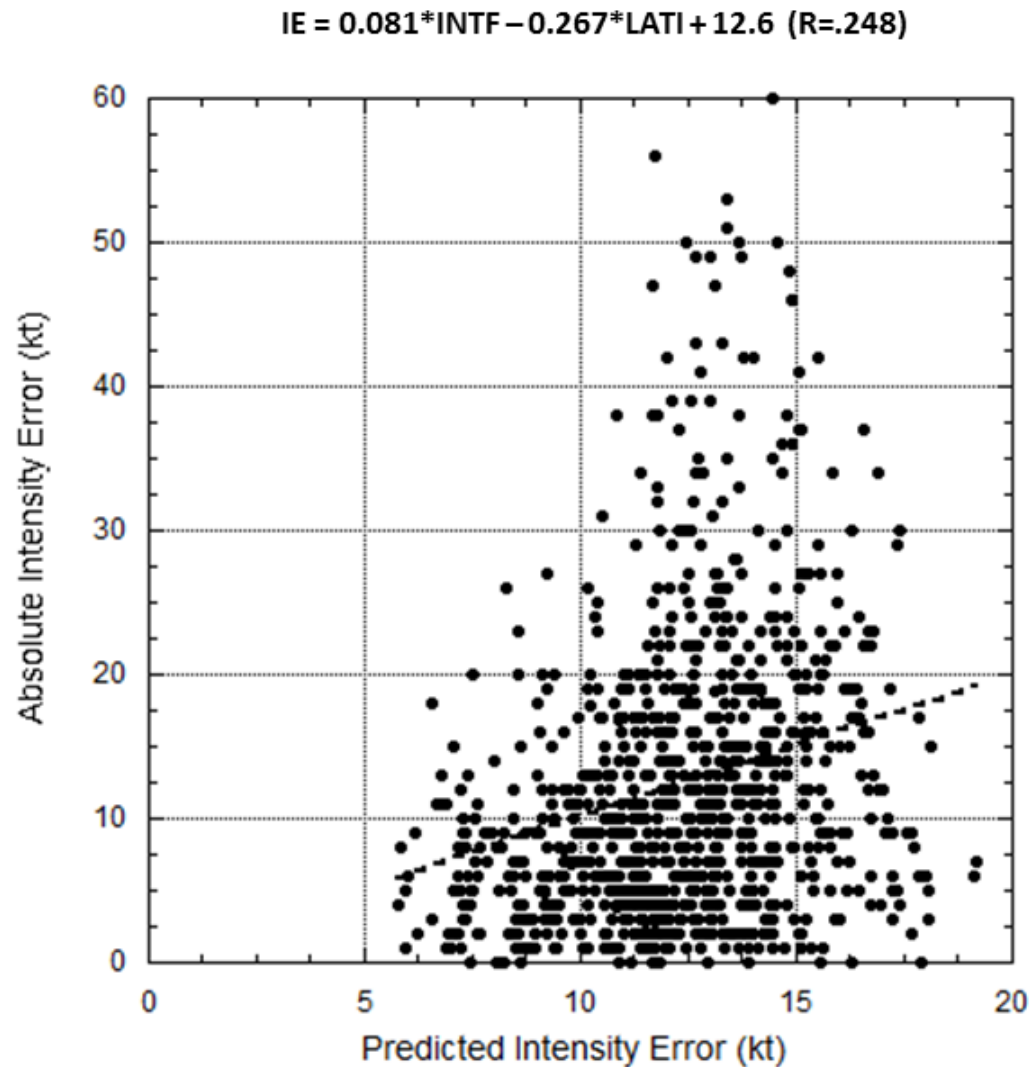
*Naval Research Laboratory, Monterey, California*

(Manuscript received 22 May 2013, in final form 16 December 2013)

### ABSTRACT

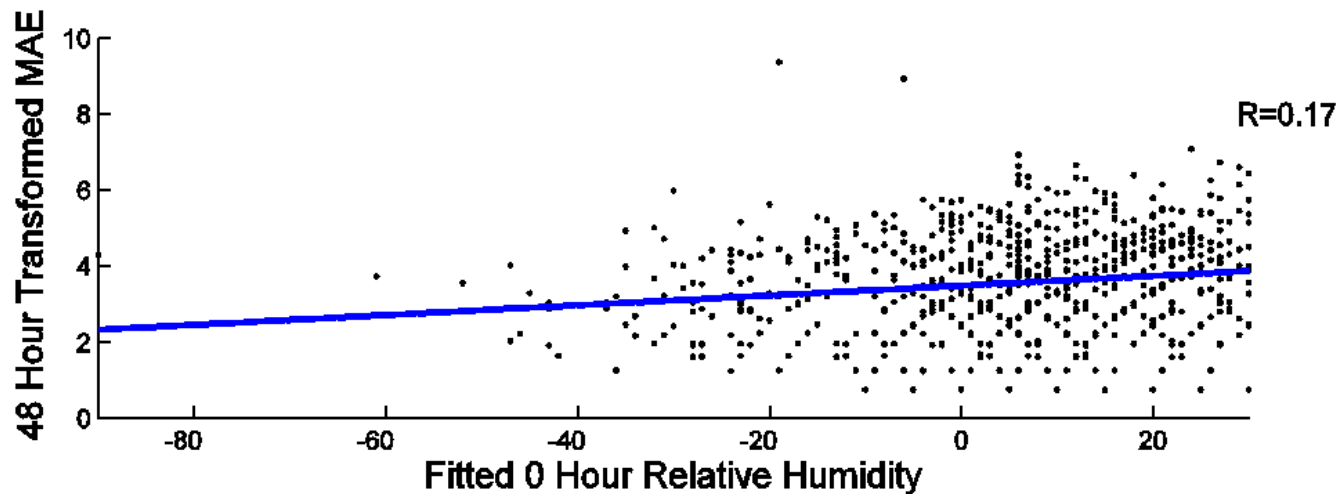
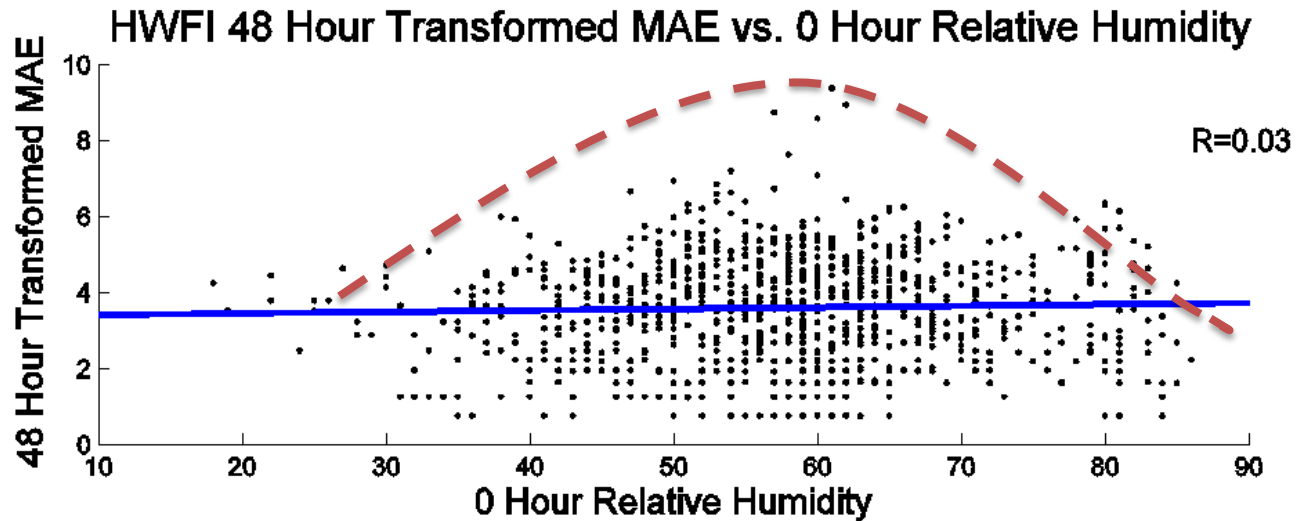
The extent to which the tropical cyclone (TC) intensity forecast error of IVCN and S5YY, consensus models routinely used by forecasters at the National Hurricane Center and the Joint Typhoon Warning Center, respectively, can be predicted is determined. A number of predictors of consensus intensity forecast error, which must be quantities that are available prior to the official forecast deadline, were examined for the Atlantic and eastern North Pacific basins for 2008–11 and the western North Pacific basin for 2012. Leading predictors were found to be forecast TC intensity and intensity change, initial intensity and latitude of the TC, and consensus model spread, defined to be the average of the absolute intensity differences between the member forecasts and the consensus forecast. Using stepwise linear regression and the full pool of predictors, regression models were found for each forecast length to predict the IVCN and S5YY TC intensity forecast errors. Using the regression models, intervals were determined centered on the IVCN and S5YY forecasts that contained the verifying TC intensity about 67% of the time. Based on the size of these intervals, a forecaster can determine the confidence that can be placed upon the IVCN or S5YY forecasts. Independent data testing yielded results only slightly degraded from those of dependent data testing, highlighting the capability of these methods in practical forecasting applications.





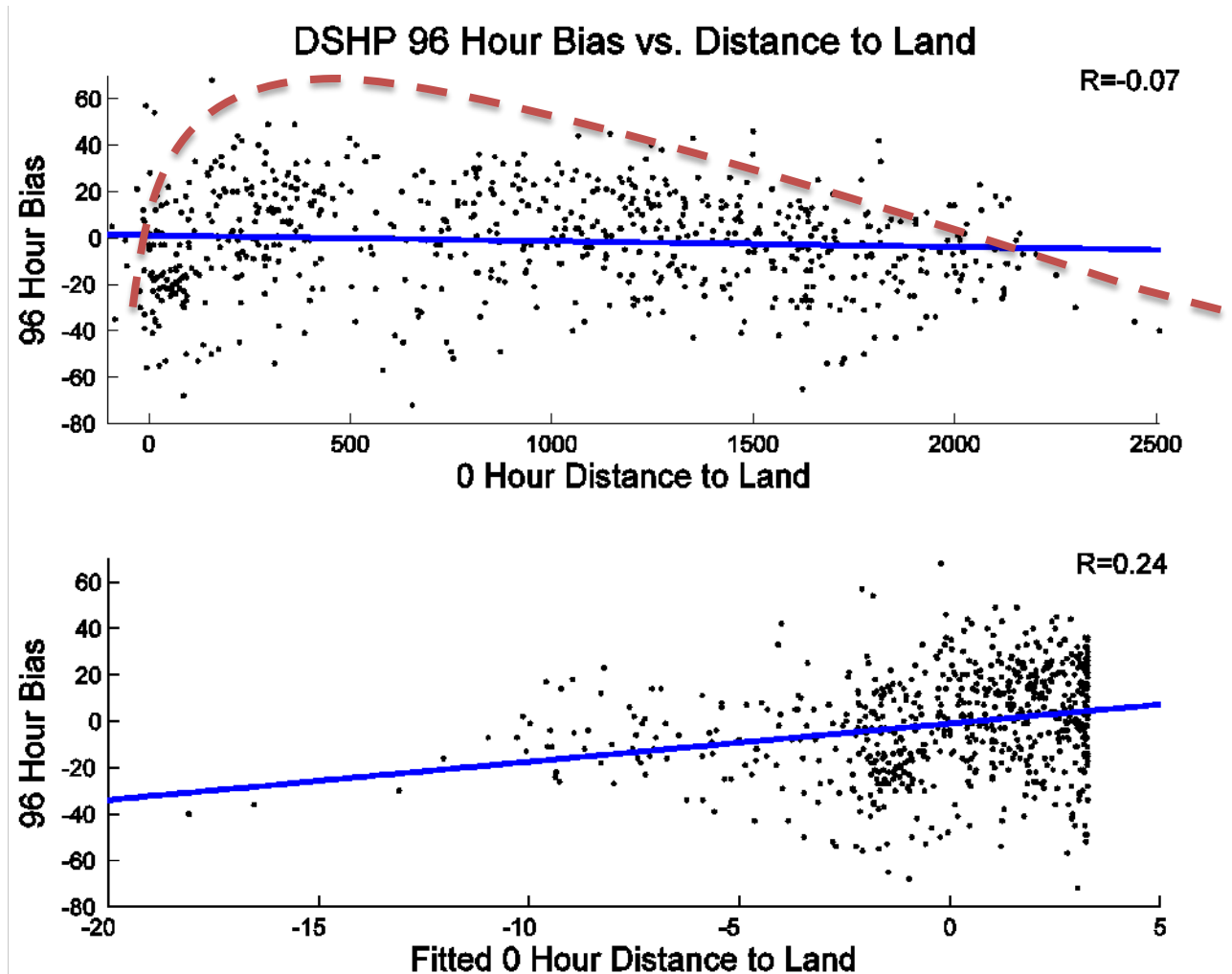
“For the Atlantic basin, the percent variance of IVCN TC absolute intensity forecast error that could be explained for this independent sample ranged from 2-5% compared with 4-6% for the dependent sample”

# Boutique Predictors: Gaussian Fit of Relative Humidity vs. AE

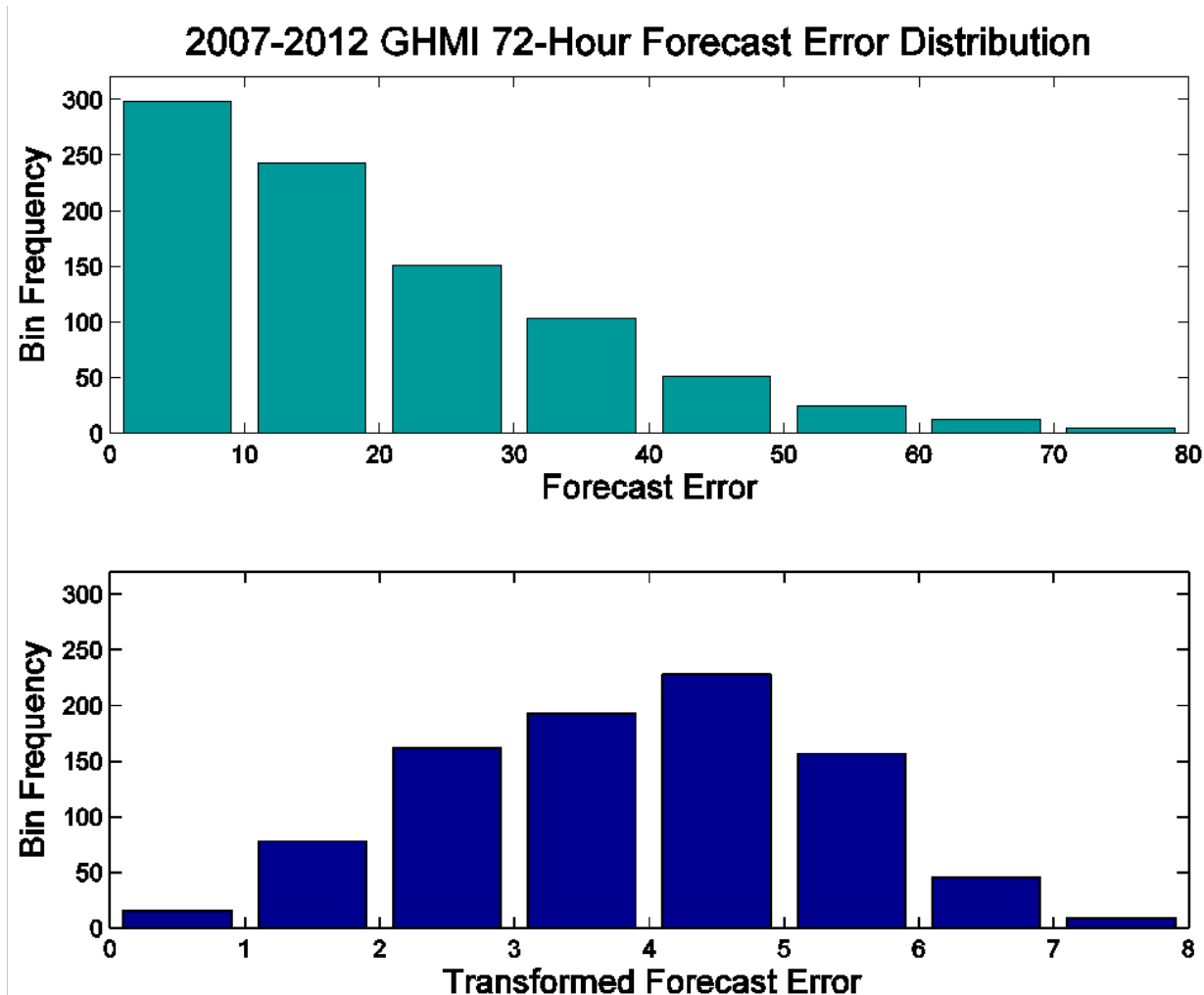


# Boutique Predictors: 2<sup>nd</sup> Order Polynomial

## Fit of Dist. To Land vs. Bias



# Example of AE Transformation



# Methodology: Nonlinear Fits of Predictors

- Several predictors exhibiting nonlinear relationships with error were empirically fit
- Functions tested: Gaussian, second order Gaussian, second order polynomial, and third order polynomial
- 0-Hour Latitude, 0-Hour distance to land, and 0-Hour Relative Humidity exhibited the strongest non-linear relationships

# 2014 RESULTS

# Percent Improvement Over AE Climatology Forecasts

# of Cases	Hours	LGEM	DSHP	HWFI	GHMI
133	12	12.3	13.2	14.8	14.4
117	24	19.3	15.8	12.9	13.8
102	36	16.3	19.5	8.2	10.7
86	48	14.0	12.6	9.6	10.2
74	60	17.3	17.7	28.9	28.3
64	72	6.1	8.1	16.4	14.7
53	84	6.1	6.4	13.1	11.1
42	96	8.5	7.6	17.3	18.0
34	108	11.3	-8.9	30.2	28.8
28	120	18.7	8.5	43.5	39.7

# Percent Improvement Over Bias Climatology Forecasts

# of Cases	Hours	LGEM	DSHP	HWFI	GHMI
133	12	-1.1	-1.5	1.5	0.7
117	24	5.0	3.4	11.1	9.8
102	36	13.4	2.4	15.6	14.1
86	48	16.4	4.3	7.8	6.4
74	60	18.0	5.4	5.9	5.2
64	72	28.9	8.6	6.4	6.2
53	84	23.9	9.0	7.9	7.4
42	96	15.3	0.9	15.2	14.7
34	108	8.0	-1.4	19.6	20.3
28	120	-1.2	7.4	47.3	47.2