Integrated Modeling of Hurricane Impacts on Power Systems in a Changing Climate

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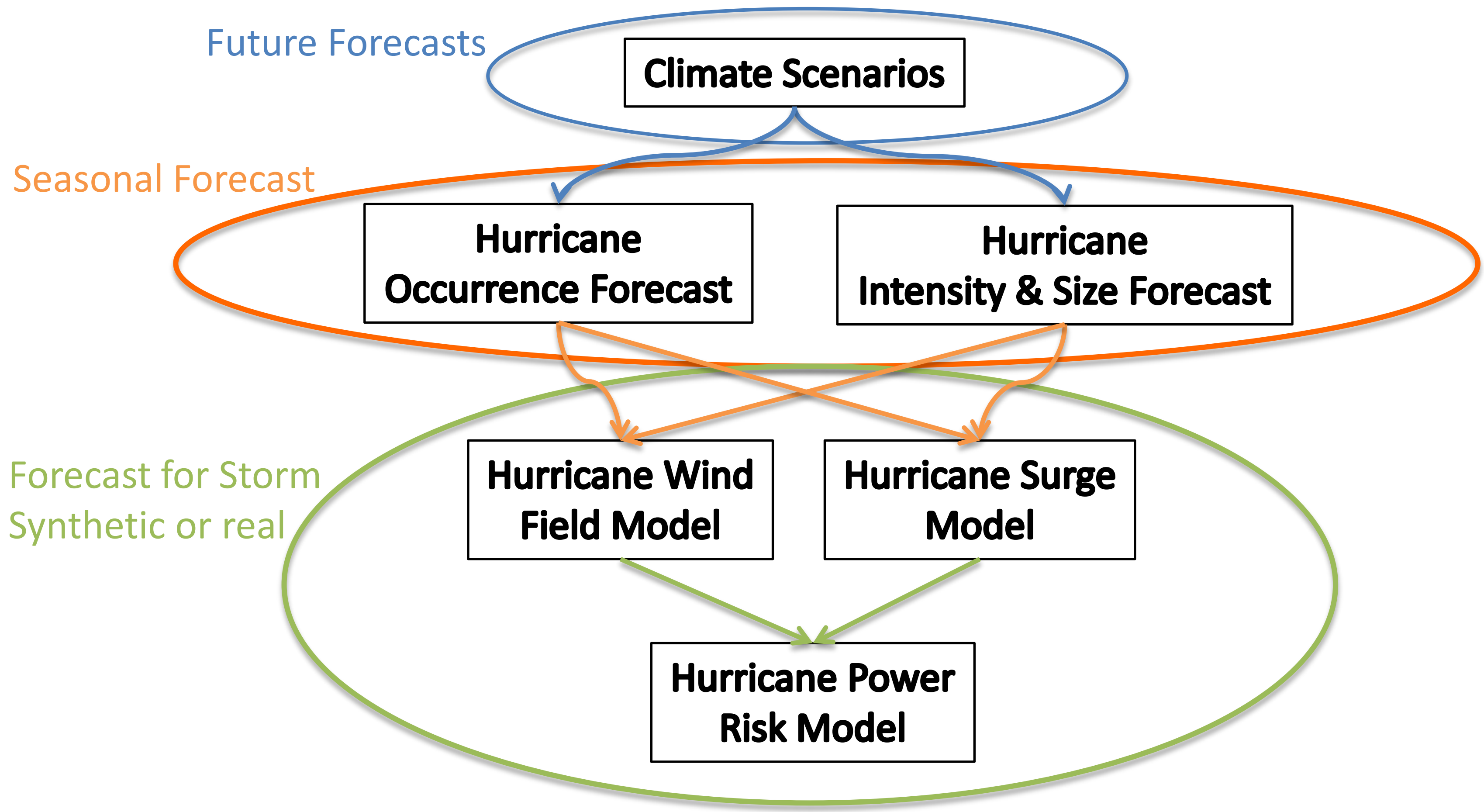
Climate – Hurricanes – Power Systems

Overarching Goal: Estimate changes in long-term risk to power systems from hurricanes in a changing climate

Main Components:

1. Seasonal hurricane modeling and forecasting
2. Hurricane surge modeling
3. Hurricane power outage modeling
4. Long-term risk estimation

Project Structure



Prior Seasonal Hurricane Forecasting

General Characteristic:

–Variety of statistical methods, varying degrees of rigor

–Use small number of pre-selected variables

–Focus on model fit -> predictive abilities of models not particularly good upon re-examination

Typical Papers:

Paper	Model(s) Used	Covariates Used
Elsner et al. (2007)	Poisson GLM, ARIMA	SST
Elsner et al. (2008)	Quantile regression	None
Sabbatelli & Mann (2008)	Poisson GLM	SOI, SST, NAO
Saunders & Lee (2008)	OLS	SST, Wind Shear
Klotzbach & Gray(2009)	Stepwise Regression	SST, SLP, Wind Shear

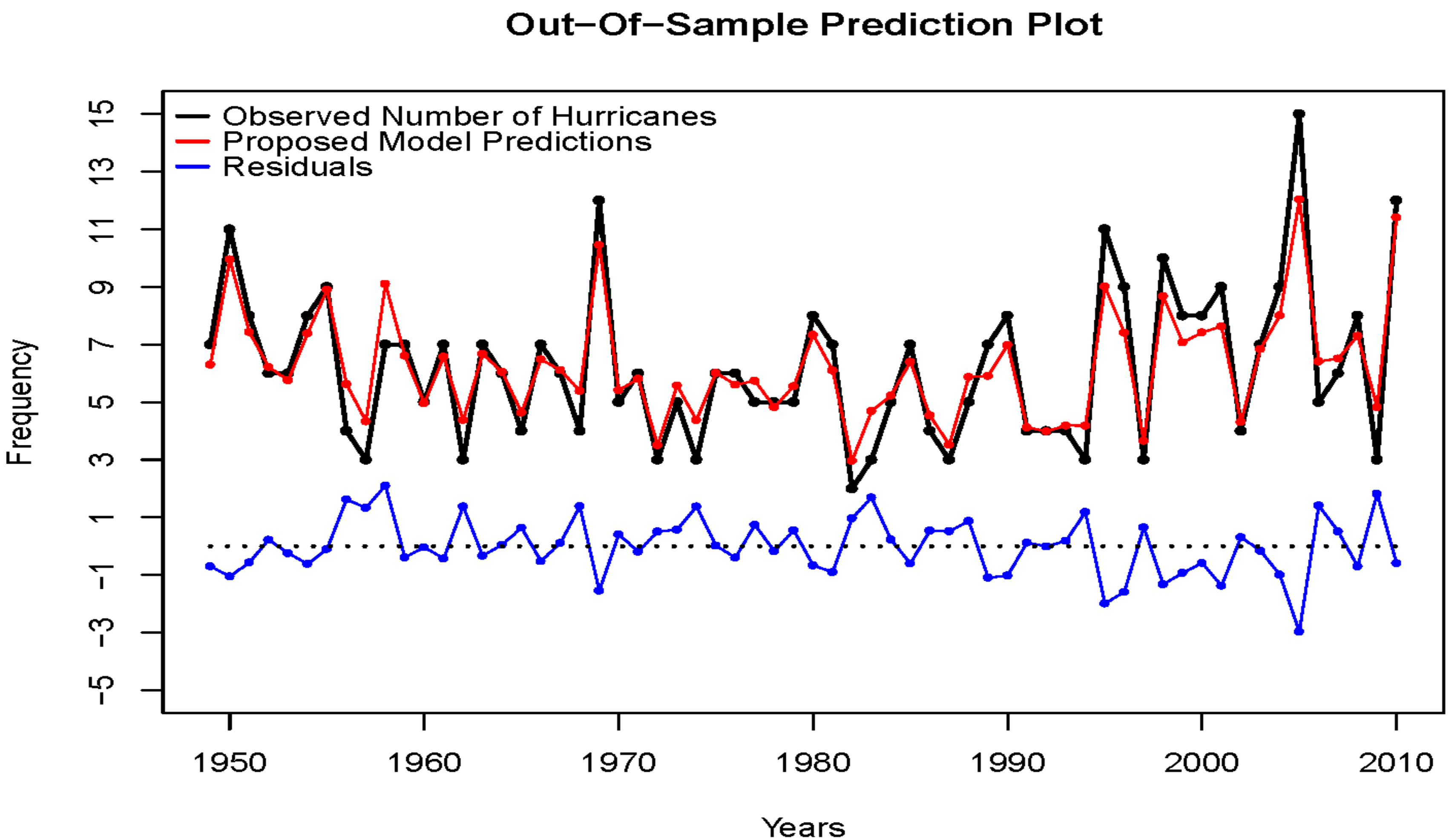
Seasonal Count Forecasting: A New Approach

- Used broad range of climate variables rather than pre-screening based on expert knowledge or correlation
- More flexible, non-linear data miner (Random Forests) to maximize predictive accuracy
- Trained with 1948-2009, 30-fold 20% random holdout cross validation
- Compared with existing models from the literature

<u>Example Comparison </u>(Klotzbach & Gray model: hold-one out validation)

Approach (1984-2008)	Mean Absolute Error	Correlation of Prediction with Actual Count
Klotzbach & Gray June	1.5	0.78
Klotzbach & Gray August	1.3	0.82
Our Model	0.8	0.97

Forecasting Validation Results



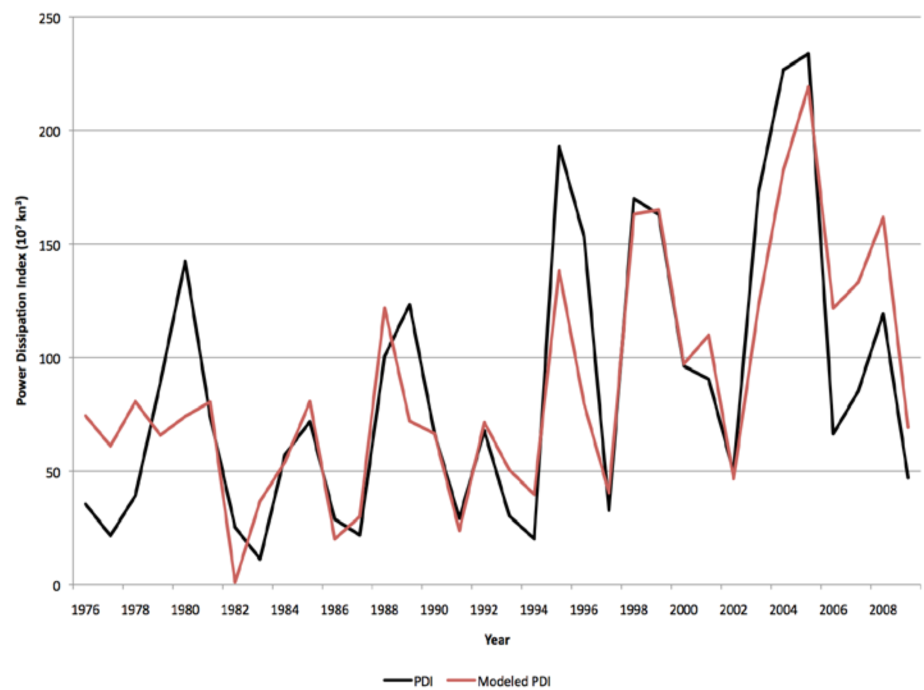
Modeling TC Intensity

-Purpose: develop models to explain interannual variations in mean Atlantic TC intensity, as measured by Power Dissipation Index (PDI), percentage of intense hurricanes, Vmax, and per storm PDI and to identify important environmental and storm-related variables

-Generalized Additive Models (GAMs) were developed using 9 different variables including: relative SST (RST), Nino3.4 SST (ENSO), Genesis Potential Index (GPI), Maximum Potential Velocity (MPV)

Intensity measure	Predictors	R^2	RMSE abs.	RMSE [σ]	MAE abs.	MAE [%]	AICW
Vmax	RST, ENSO	0.46	3.90	0.72	3.13	6.31	0.26
	ENSO, GPI	0.39	4.13	0.77	3.34	6.75	0.58
Number	ENSO, MPV	0.88	1.56	0.34	1.25	10.91	0.92
Percent	SHR, ENSO	0.55	6.39	0.66	5.29	44.41	0.75
ssaPDI	ENSO, MPV	0.40	2.70	0.77	2.29	32.86	0.44
PDI	ENSO, MPV	0.72	32.84	0.53	25.37	29.17	0.90

Statistical results of GAM models for all intensity measures. Chosen predictors, Coefficient of determination (R^2), absolute RMSE, RMSE in units of σ, MAE and MAE in % of the mean, AIC Weight (AICW).



Predicted PDI (red) based on GAM vs. Observed PDI (black)

Modeling TC Size: Methods

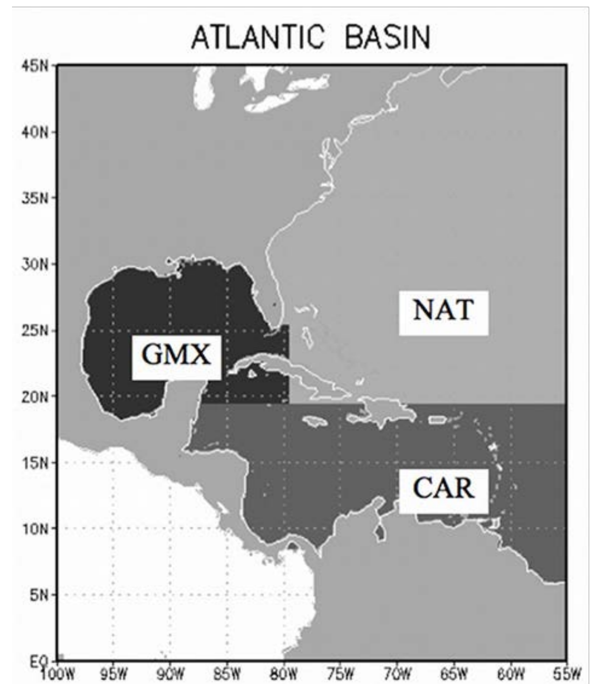
-Purpose: develop models to explain interannual variations in mean Atlantic TC size, as measured by radius of maximum winds (RMAX) and radial extent of 34 knot winds (17 m s^{-1}; R34), and to identify important environmental and storm-related variables

-TC size data for the Atlantic basin were derived from Extended Best Track Data (1988-2008)

-Stepwise multiple linear regression models were developed for the entire Atlantic and each sub-basin

Table 1. Variables Considered for Their Potential Influence on Tropical Cyclone (TC) Size

Abbreviation	Description
VMAX	maximum surface tangential velocity (kt)
TCLAT	TC latitude (°N)
TCSPD	TC forward speed (kt)
SST	sea surface temperature (°C)
MSLP	mean sea level pressure (mbar)
RHUM	600 mbar relative humidity (%)
VOR	850 mbar vertical vorticity ($\times 10^{-5}$ s^{-1})
VSHR	850–200 mbar vertical shear (kt)
N34	Niño 3.4 SST anomaly (°C)



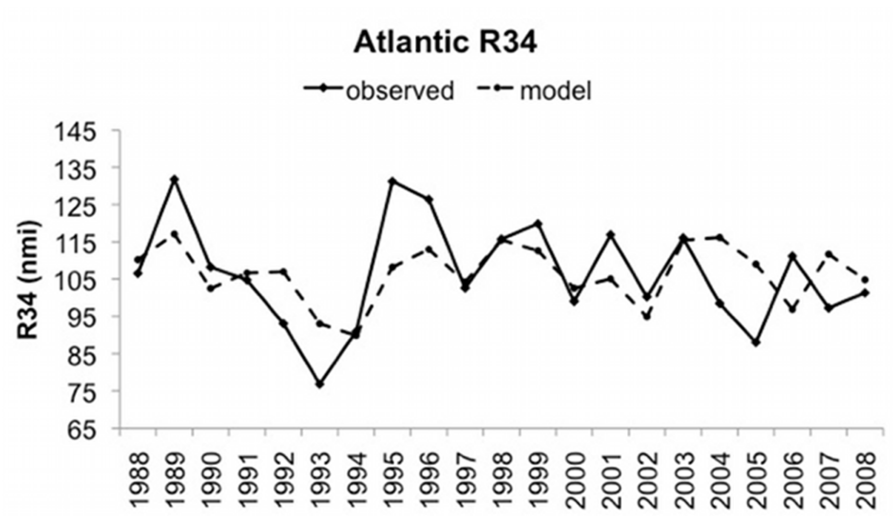
Quiring, S. M., Schumacher, A. B., Labosier, C., and L. Zhu (2011) Variations in mean annual tropical cyclone size in the Atlantic. *Journal of Geophysical Research–Atmospheres*, 116, D09114, doi:10.1029/2010JD015011.

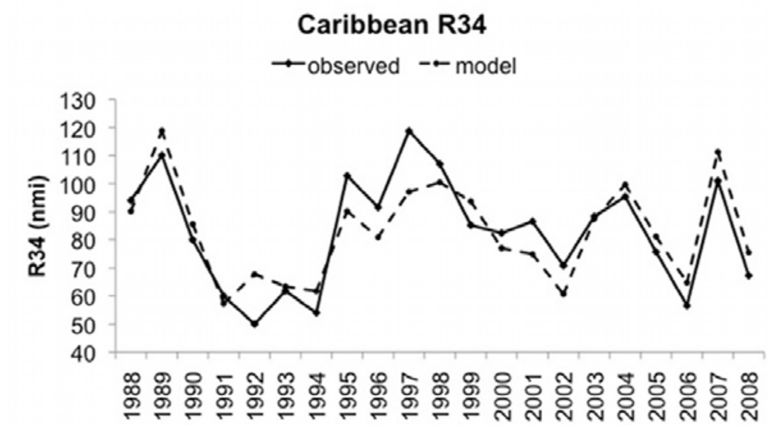
Modeling TC Size: Results

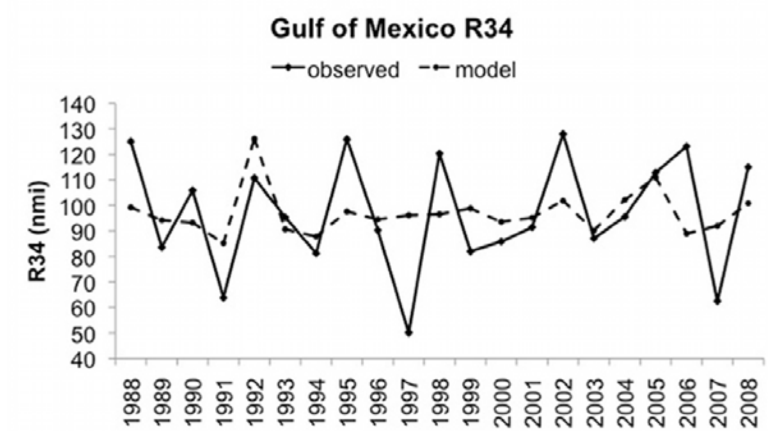
-Explained up to 75% of the variance in TC size, but relationships vary among the sub-basins and therefore it is inappropriate to develop a single model

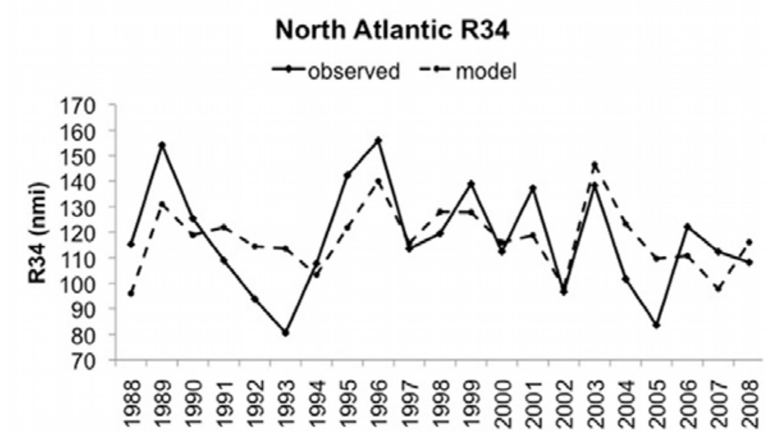
-Maximum tangential wind (VMAX) is the most important variable for explaining variations in mean annual TC size

-Other factors such as sea surface temperature, sea level pressure, and Niño 3.4 also influenced mean annual TC size









Surge Response Functions General Form

General form for maximum surge response:

$$\zeta_{\max}(x) = \phi\left(x, x_o, c_p, R_p, \theta, v_f\right) + \varepsilon$$

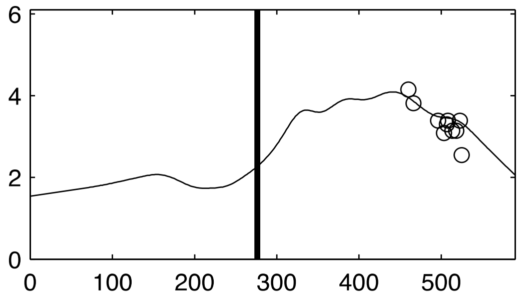
$$\varepsilon^2 = \varepsilon^2_{tide} + \varepsilon^2_{surge\ simulation} + \varepsilon^2_{waves} + \varepsilon^2_{winds} + \ldots$$

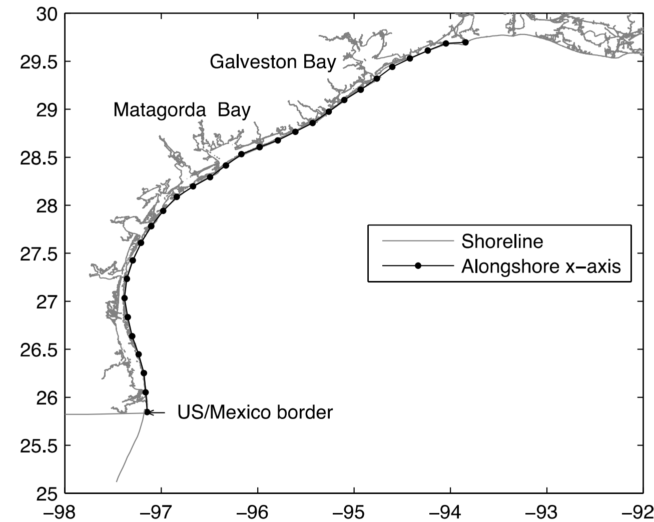
where:

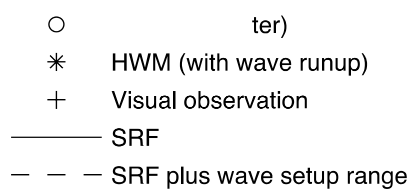
ϕ is a continuous surge response function
x is location of interest
x_o is landfall location
c_p is hurricane central pressure near landfall
R_p is hurricane pressure radius near landfall
θ is hurricane track angle with respect to the shoreline
v_f is hurricane forward speed near landfall
ε is uncertainty in the surge response

From Resio, Irish, and Cialone, 2009, *Nat. Hazards*

Surge Response Functions: Validation

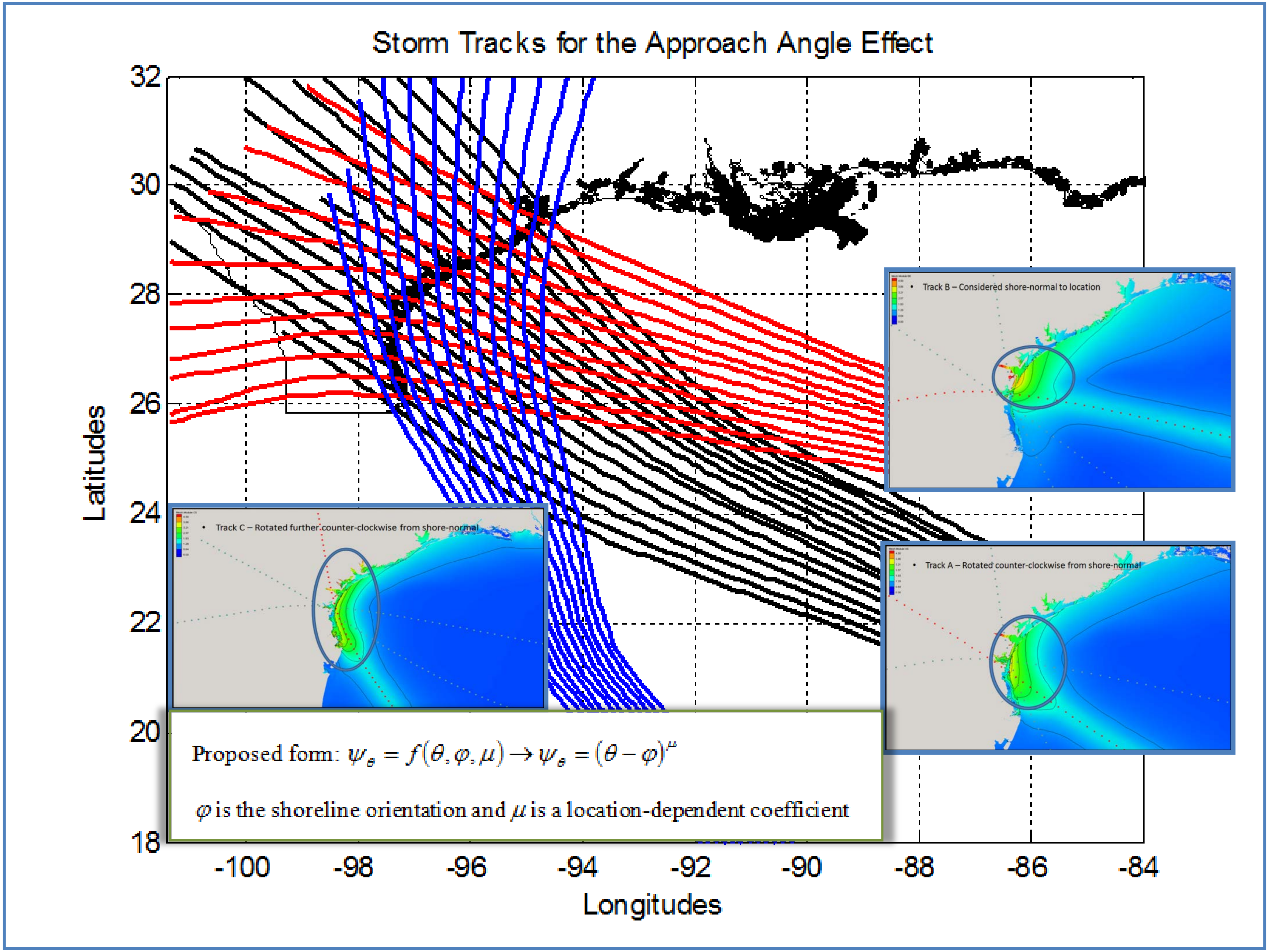






- Time to produce: 5 seconds in Fortran on one 3.2-GHz Xeon processor

From Irish et al., 2011, *Geophys. Res. Lett.*


Storm Tracks for the Approach Angle Effect
Latitudes
32
30
28
26
24
22
20
18
Longitudes
-100
-98
-96
-94
-92
-90
-88
-86
-84
Track B – Considered shore-normal to location
Track C – Rotated further counter-clockwise from shore-normal
Track A – Rotated counter-clockwise from shore-normal
Proposed form: $\psi_\theta = f(\theta, \varphi, \mu) \rightarrow \psi_\theta = (\theta - \varphi)^\mu$
φ is the shoreline orientation and μ is a location-dependent coefficient

Power Outage Forecasting During Hurricanes

Prior Work

<u>Outages</u>

Liu et al. (2005): a first model

Liu et al. (2008): accounting for spatial correlation

Han et al. (2009a, 2009b): improved accuracy, usability

Guikema & Quiring (*under review)*: improved accuracy

<u>Customer Meters Out</u>

Nateghi et al. (*under review)*: first customer-out model

<u>Outage Duration</u>

Liu et al. (2007): a first model

Nateghi et al. (2011): improved predictive accuracy

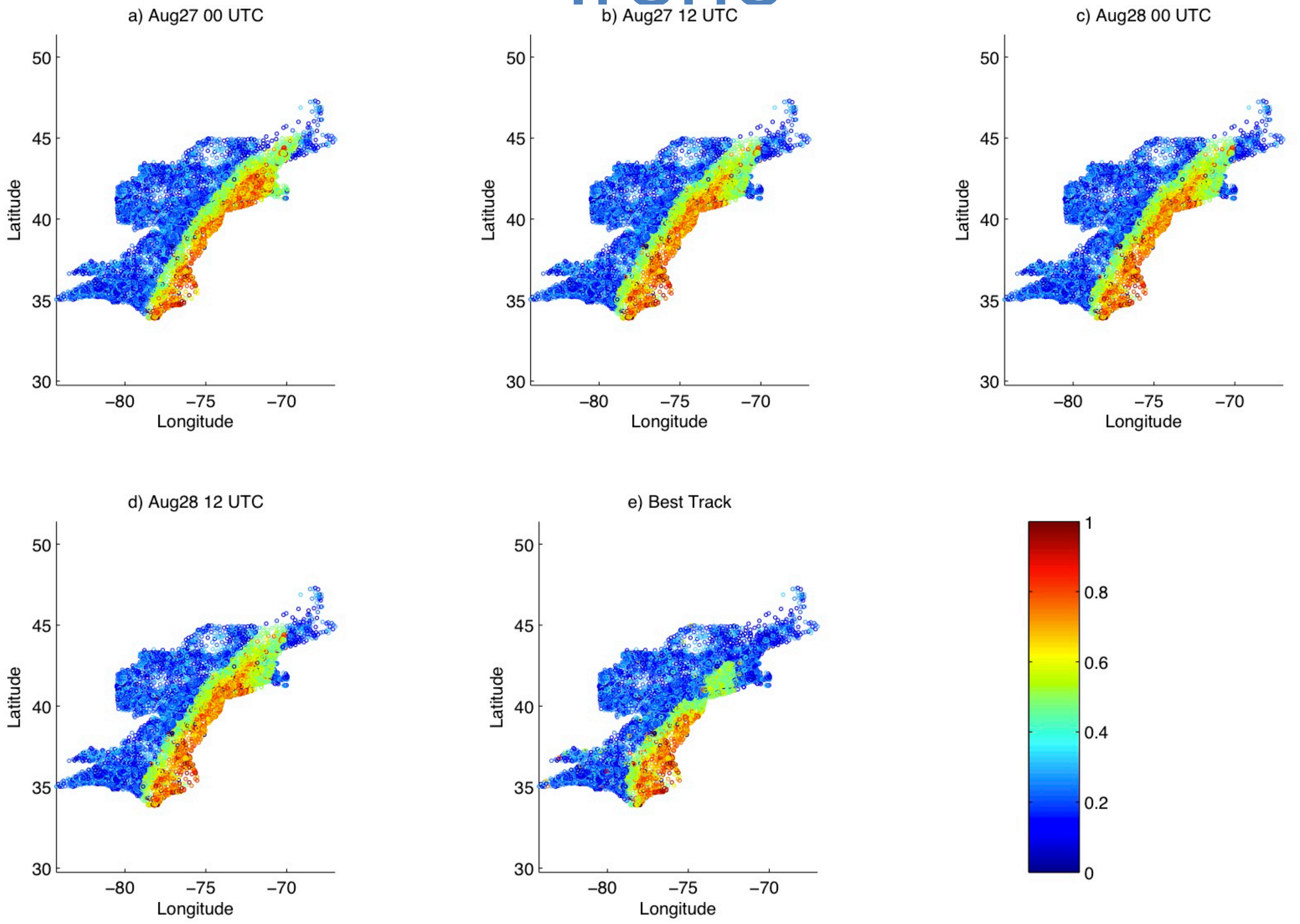
Challenge: All previous work was specific to a utility company service area and used private utility data.

Spatial Generalization

<u>General Approach</u>

1. Work within utility service area, eliminate private data, cross-validate w/in area
2. Cross-validate to other nearby states with strong outage data
3. Apply full coast, compare to actual storm outages

Example Predictions: Hurricane Irene



How Did We Do?

Gulf region validation testing

Model	Predicted Fraction Out	Actual Fraction Out	Error
Training state 30-fold cross-validation	0.46	0.46	<0.001
Katrina, Mississippi	0.51	0.49	0.02
Ivan, Georgia	*0.41*	*0.13*	*0.30*
Ivan, Mississippi	0.39	0.41	0.02
Dennis, Georgia	*0.39*	*0.24*	*0.15*
Hanna, Georgia	0.06	0.06	<0.001
Jeanne, Georgia	0.03	0.04	0.02
Katrina, Georgia	0.02	0.01	0.01
Isidore, Georgia	0.02	0.003	0.017
Cindy, Georgia	0.01	0.01	<0.001
Frances, Georgia	*0.01*	*0.30*	*0.29*

Prediction Accuracy for Hurricane Irene

State/Service Area	Model Estimate	Peak Percentage Without Power
Connecticut	48%	44%[*]
Delaware/Delmarva Pen.	*57%*	*42%*[**]
District of Columbia	22%	13%[*]
Maine	21%	15%[*]
Maryland	30%	36%[*]
Massachusetts	26%	19%[*]
New Hampshire	22%	20%[*]
New Jersey	*37%*	*24%*[*]
New York	*40%*	*12%*[*]
North Carolina	*53%*	*30%*[**]
Pennsylvania	*30%*	*13%*[*]
Rhode Island	*23%*	*65%*[*]
Vermont	21%	12%[*]
Virginia	*44%*	*29%*[*]
Baltimore Metro	*23%*	*37%*[**]
Richmond Metro	*56%*	*76%*[**]

<u>Initial Assessment</u>

-Prediction accuracy generally very good in Gulf cross-validation. 3 outliers.

-Prediction reasonable for Irene except for Rhode Island, NYC, NC

Next Step: Long-Term Risk Estimation

- Simulate synthetic storm histories for different climate scenarios
- Estimate track, wind field, surge for each storm
- Estimate power outage risk for each storm
- Comparison of long-term outage risk under different climate scenarios